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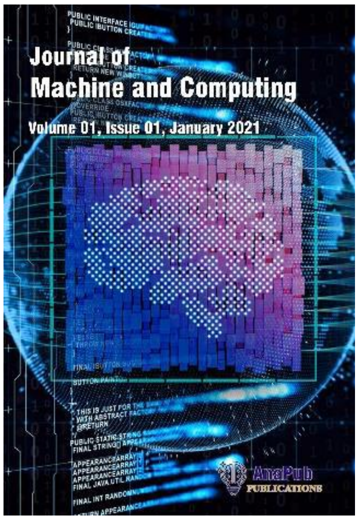

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An Oral Healthcare Recommendation Framework Using Lion-Inspired Feature Optimization and SVM Classification

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Abstract

Oral health care is indispensable for patients with insulin resistance. This research work presents a novel framework for oral implant recommendation for insulin resistant patients. This framework recommends optimal implant types and customized preoperative strategies which are contemplated for such patients. This framework integrates a synthetic patient data modelling with more clinically significant features like HbA1c, bone density and glycemic control indicators. 3000 data which mimics the clinical data is generated and with which the model is trained. The features are optimized using a Lion's Pride Inspired Algorithm (LPIA) which imitates the behavioural traits of Lions in their pride. The method of elitism is adopted for obtaining the optimal solution set. The classification is done by using Support Vector Machine. This combo demonstrated a strong performance with LPIA optimized feature space achieving a maximum classification of 81% and F1 weighted score up to 0.31. The ROC analysis was also performed for the implant types like Zirconia which produced AUC scores above 0.90 which validates the discriminatory capacity of the proposed framework. In addition, the clinical recommendation regarding the implant timing, glycemic management were generated dynamically. These results demonstrate the capability of the proposed framework as an intelligent, interpretable and patient specific decision support tool for dental implant planning in diabetic care.

Keywords—. Lion's Pride Inspired Algorithm, SVM, Oral Health care, F1 Score

1. Introduction

Recent days, an aesthetically pleasing solution for edentulism and oral rehabilitation is Dental implants. The success of the dental implant is influenced by various factors. These factors include systemic and local factors. Among the factors contributing for the success of dental implant diabetes mellitus (DM) is a prime risk contributor. This has been documented very well in literatures [1]. DM affects the wound healing and compromises bone metabolism thereby increasing the risk of peri-implantitis and implant failure. When there is a condition of poor glycemic control, this complications occur [2], [3]. Diabetes prevalence is considerably raising and it is projected that over 700 million people would be affected by DM by 2045 [4]. This gives rise to a urgent need for an evidence based decision making support system for dental care. It is factual that DM patients require a very careful risk assessment before the dental implant therapy. This involves clinical judgement which is based on blood glucose levels like HbA1c, FBS, also, bone density and systematic conditions [5]. This judgement and evaluation is not standardized and are subjective which results in an inconsistent outcomes of dental implant therapy.

In this era, machine learning (ML) has potential application in and can assist several tools in medical and dental diagnosis. This ML offers objective pattern recognition and decision making capabilities [6]. In the field of implantology, the application of ML is inevitable and have shown significant contribution in predicting and recommending implant bone loss [7]. Also in predicting treatment outcomes [8] and complication risks. Most of the available models rely on real world clinical data which is often very low in volume and also heterogenous. This data is more subjective to privacy concerns making it more hard to generalize or deploy widely. There are few frameworks that combine clinically observed facts and with the data driven intelligence. This, however, limits the adoption by dental practitioners who are concerned about transparency and trust in the recommendation [9]. These limitations are addressed by the proposed framework for recommendation specifically contemplated on dental implant for diabetic patients. The proposed framework leverages a synthetic data generation which can be scaled and which is flexible. The framework employs a naturally inspired algorithm based on the behavioural traits of Lion to optimize the features. This proposed algorithm mimics the social behaviour of Lions for robust feature selection. Naturally inspired algorithms work very well for optimization. Finally a Support Vector Machine (SVM) classifier which is well known for its high accuracy is used. The framework is implanted as a GUI which enabling a real time input and a visual feedback and a report generation. The framework provides outputs like implant type suitability, recommended loading protocol. This can be immediate or delayed. Also preoperative caution level which is low, moderate, high. Finally glycaemic control recommendation also. This proposed framework is a recommendation system for complete dental decision support pipeline which integrating data science along clinical reasoning. This framework offers a reproducible, explainable and a practical tool for dental professionals in situations where access to a very large patient dataset is scarce.

This proposed work presents a framework in its entirety including mathematical modelling, synthetic data strategies, optimization, logic, classification pipeline, user interface design and an output visualization. The major objective is to demonstrate a potential of the framework as a scalable patient centric, AI enhanced implant recommendation system which lay the groundwork for future clinical deployment.

Structure of the Paper- The rest of the paper is organized as follows: Section 2 discusses mathematical modelling, and Section 3 provides synthetic data for dental implant of diabetic patients. In Section 4 feature optimization using proposed lion's pride inspired algorithm is provided. Section 5 contains Experimental results and Interpretations and Section 6 contains conclusion.

2. Mathematical Modelling

This section provides the mathematical modelling of the proposed framework. The framework solves the complex and multi-dimensional problem of decision making in dental implant recommendation for diabetic patients. The mathematical modelling of the synthetic data generation, the actual problem, feature encoding and normalization and finally probabilistic prediction is provided in this section. This modelling attempts to simulate realistic profiles and translates them in to analyzable feature space and eventually learn a reliable decision function for recommendation.

2.1 Synthetic Data Generation

Let us consider the entire psychological space for the patients as in eqn. (1).

$$X = \left\{ x \in R^d \mid x_j \in \Omega_j \forall j = 1,2, \dots d \right\} \quad (1)$$

Where d is the number of attributes like FBS, Bone density, HbA1C etc. And, $\Omega_j \in R\ U\ C_j$ is the valid domain for the feature x_j which can be numerical or categorial.

The feature wise distribution, for each given continuous variable $x_j \epsilon R$, a probability distribution is assigned P_j which is based on clinical studies. Let us consider HbA1c, the variable x_{Hb1c} ~N ($\mu = 7.5, \sigma^2 = 0.8$); similarly, for FBS x_{FBS}~N$(150, 30^2)$, and for bone density x_{BD}~ ⊔ (0.1, .5). where N denotes the normal distribution and ⊔ denotes the uniform distribution. Also, the categorial variables $x_k \in C_k$, are assigned a discrete probability mass function P_k.

$$P_k(C_i) = \Pr(x_k = c_i), \sum_i P_k(c_i) = 1 \tag{2}$$

Also, in the multivariate generation, let $x_i \sim P(x)$, where

$$P(x) = \prod_{j=1}^{d} P_j(x_j) \tag{3}$$

Here we assume independence. And we generate N synthetic samples

$$D_{syn} = \{x_i \sim P(x)\}_{i=1}^{N} \tag{4}$$

The label assignment function $y = g(x)$ assign implant types based on the clinical rules

$$y_i = g(x_i) = \begin{cases} Zirconia, if\ x_{HbA1c} < 7.5\ and\ x_{BD} > 0. \\ Titanium, \quad otherwise \end{cases} \tag{5}$$

An alternate method for probabilistic labels can be sampled from eqn.6 which is the softmax model which provides better variability and non-deterministic decision boundary simulation.

$$P_r(y = c_k | x_i) = \frac{\exp(\theta_k^T x_i)}{\sum_j exp(\theta_k^T x_i)} \tag{6}$$

2.2 Problem Formulation

Let $D = \{(x_i, y_i)\}_{i=1}^{N}$ be the complete synthetic dataset, it is anticipated to model the dental implant recommendation framework, as a supervised classification problem.

$$Given: x_i \in R^d, Predict: y_i \in Y \tag{7}$$

Where $Y = \{Zirconia, Titanium, Delay, Immediate\}$

The objective is to learn a classifier $f: R^d \to Y$ that would minimize the misclassification loss.

2.3 Label Encoding and Dimensional Homogenization

The dataset which is used for training the algorithm has to be uniform and to ensure the uniformity, label encoding is used where;

$Label\ Encoding$: $\emptyset: C_j \longrightarrow Z$ for categorial features is given as;

$$x_j = c => x_j^{enc} = \emptyset(c) \tag{8}$$

In addition, the continuous features are standardized using Z-Score normalization which can be given as ;

$$x' = \frac{x_j - \mu_j}{\sigma_j} \tag{9}$$

In eqn. (9), x_j *and* μ_j are the empirical mean and standard deviation of the feature *j*. The Final transformed input space is given as :

$$X' = \{x_j' \in R^d \mid x_j' = \begin{cases} encoded\ (x_j), x_j \in C_j \\ \frac{x_j - \mu_j}{\sigma_j}, x_j \in R \end{cases} \tag{10}$$

2.4 Objective Function of the Prediction Model

It is imperative to model the objective function of the prediction model mathematically. Let $f_\theta(x)$ represents the parametric decision function which is trained on the labelled data. In this case, SVM. The overall objective is to minimize the empirical risk which can be given as:

$$R'(f) = \frac{1}{N}\sum_{i=1}^{N} l(f(x_i'), y_i) \tag{11}$$

In eqn. 11, the *l* represents the 0-1 loss.

$$l(y', y) = \mathbb{I}[y' \neq y] \tag{12}$$

Which can also be represented as log loss for probabilistic models;

$$l(y', y) = -\sum_{y} \mathbb{I}[y = c]\, logPr(y = c \mid x) \tag{13}$$

2.5 Clinical Rule Modelling

In the clinical modelling, while *f(•)* provides the prediction for implant type. The real-world applicability is ensured through clinical rule modelling. It is necessary to define post inference logic as below;

$$Caution\ Level = \begin{cases} High\ , x_{HbA1c} & > 8 \\ Moderate, 7.5\ x_{HbA1c} & \leq 8 \\ Low, x_{HbA1c} & > 7.5 \end{cases} \tag{14}$$

$$Loading\ Protocol = \begin{cases} Delayed\ \ , x_{HbA1c} > 7.5\ or\ x_{FBS} > 180 \\ Immediate, \qquad otherwise \end{cases} \tag{15}$$

2.6 Classification using SVM

The classification is done using Support Vector Machine. The mathematical formulation is like, consider $\emptyset: R^d \rightarrow$ H denotes the transformation of lower dimensional input space into a higher dimensional Hibert space. The SVM attempts to solve;

$$\min_{w,b,\varepsilon} \frac{1}{2}\ ||w||^2 + C\sum_{i=1}^{N} \varepsilon_i \tag{16}$$

Eqn.16 is subject to the condition in eqn. 17

$$y_i(w^T \emptyset(x_i) + b) \geq 1 - \varepsilon_i, \varepsilon_i \geq 0 \tag{17}$$

The parameter C is the regularization parameter and ε_i is the slack variable. Also, here we use RBF kernal;

$$K(x_i, x_j) = \exp(-\gamma||x_i - x_j||^2) \tag{18}$$

It has to be noted that the output is both a class label $y' \in \Upsilon$ and the confidence score is given by plat scattering.

2.7 Evaluation Metric

The evaluation metric can be modelled as : let, $\mathrm{T} = \{(x_i, y_i)\}_{i=1}^{T}$ be the test set. In this case, the accuracy can be defined as the following;

$$Accuracy = \frac{1}{\mathrm{T}}\sum_{i=1}^{T} 1(f(x_i) = y_i) \tag{19}$$

Also, the probabilistic confidence can be defined as;

$$Confidence\ (x) = \max_{y \in Y} P(y \mid x) \tag{20}$$

In the overall computations, there are few assumptions made. The patient distribution is assumed to be stationary and representative. In addition, the synthetic data approximates the underlying joint distribution. Moreover, the noise in the measurements is a function of gaussian distribution.

Once the classification is complete, a rule based post processing layer using SVM refines the observed decision based on the critical indicators such as HbA1C and bone density. The recommendations include (i) Implant timing : Delayed or Immediate (ii) Loading Protocol : Immediate or Delayed loading (iii) Preoperative Caution level : Low, Moderate and High (iv) Glycemic control advice : Proceed normally and Refer to endocrinologist.

3. SYNTHETIC DATA FOR DENTAL IMPLANT OF DIABETIC PATIENTS

The fact that limit predictive models in healthcare, particularly in situations such as dental implant recommendation for diabetic patients is the non-availability of well- organized and diverse clinical datasets. Real world data a primarily restricted due to the fact of privacy, heterogenous data collection standards and under representation of patient subgroups [11]. In the arena of diabetic patients who require dental implants, the challenges gets elevated due to the systematic conditions like hyperglycemia compromised bone healing and localized dental health factors. These challenges are overcome through synthetic data generation which augment limited datasets and thereby simulating various clinical scenarios [12], [13].

3.1 Necessity of Synthetic Data in Dental Implant Prognostics

Dental implants are often affected by Diabetes which is a significant risk factor affecting the prognosis. This happens due to impaired osseointegration and deferred wound healing [14]. There are studies [15] which suggests that there are quantitative relationship between diabetic biomarkers and implant success rate. This data scarcity results in underpowered models and unreliable predictive performances. Synthetic data solves these problems. Synthetic datasets are generated by statistical simulation wherein every feature are modelled by using probability distribution functions which are derived from real world scenarios [16]. Synthetic data avoids concerns related to privacy [21]. This ensures synthetic data are used to train predictive models which corelates to clinical data [22]

3.2 Feature wise modelling in synthetic data

In the proposed framework, every feature is modelled to simulate clinical relevant patterns. In the framework, HbA1c is modelled using gaussian distribution which centered at 7.8% with variation that reflects poor glycemic control which is seen as a failure in implant [17]. Moreover, bone density is modelled as uniform distribution to simulate various range of bone qualities from osteoporotic to a healthy cortical bone [18]. Fasting blood sugar and Random blood sugar are modelled using log normal distribution which is seen in diabetic population [19]. Multinomial distribution is used to model categorial variables [20]

TABLE I
STATİSTİCAL PROPERTİES OF FEATURES FOR SYNTHETİC PATİENT DATA GENERATİON

Feature Name	Symbol	Type	Domain / Support	Distribution	Parameters
Age	x_1	Continuous	[30, 85] years	Truncated Normal	μ=58, σ=10
Gender	x_2	Categorical (Binary)	{0: Female, 1: Male}	Bernoulli	p=0.55
HbA1c (%)	x_3	Continuous	[5.5, 12]	Normal	μ=7.8, σ=1.2
Fasting Blood Sugar (FBS)	x_4	Continuous	[80, 300] mg/dL	Log-Normal	μ=5, σ=0.25 (in log scale)
Random Blood Sugar (RBS)	x_5	Continuous	[90, 350] mg/dL	Normal	μ=170, σ=35
Bone Density	x_6	Continuous	[0.2, 1.6] g/cm³	Uniform	a=0.2, b=1.6
Smoking Status	x_7	Categorical (Binary)	{0: No, 1: Yes}	Bernoulli	p=0.25p = 0.25
Duration of Diabetes	x_8	Continuous	[0, [illegible]5] years	Gamma	k=2.5, θ=4
Hypertension	x_9	Categorical (Binary)	{0: No, 1: Yes}	Bernoulli	p=0.32
Periodontal Condition	x_{10}	Ordinal	{1, 2, 3, 4}	Categorical (Multinomial)	π=[0.15,0.35,0.30,0.20]for Healthy to Severe
Bone Quality Grade	x_{11}	Categorical	{I, II, III, IV}	Categorical (Multinomial)	π=[0.10,0.40,0.35,0.15]
Implant Site Type	x_{12}	Categorical (Binary)	{0: Maxilla, 1: Mandible}	Bernoulli	p=0.48

4. FEATURE OPTIMIZATION USING PROPOSED LION'S PRIDE INSPIRED ALGORITHM

Most of the datasets in healthcare are often filled with redundant and irrelevant features that will definitely have an impact in the predictive performance of machine learning models and when the datasets are of higher dimensional, the problem is imperative [23]. Hence feature optimization is a very important step to improve the classifier's accuracy, to reduce the computational complexity and to improvise the interpretability. In the proposed framework, a novel bio inspired optimization algorithm named Lion's Pride Inspired Algorithm (LPIA) which is customized very specifically for dental implant recommendations for diabetic patients is employed.

4.1 Motivation

The proposed LPIA algorithm is inspired from the hierarchical and competitive social behaviour of Lions. Very specifically, the traits which the lions adopt to dominate the members of the pride which is influential due to the genetic quality of the population of lions [24]. Naturally, lions maintain their pride through selective mating, competition for dominance and elimination of weaker members. These traits are taken into account while devising the LPIA. The core characteristics of the proposed LPIA is based on : Exploration – how the lions search in diverse regions of solution space through competing prides, Exploitation- how the lions retain the elite solutions (dominant lions) to converge towards optimality, Adaptive Mutation – introducing variability to avoid premature convergence. Unlike in traditional metaheuristics like Genetic Algorithm (GA) or Particle Swarm Optimization (PSO), LPIA preserves the elite group and competitive displacement which in turn reflects in the quality and complexity. This makes LPIA more adaptive for feature selection problems.

4.2 Mathematical formulation of Feature Selection problem.

The feature selection problem in the proposed framework can be modelled as;
Let $\mathrm{F} = \{f_1, f_2, f_3, \dots \dots . f_d\}$ is the set of all the available features and $\mathbb{S} \in \mathrm{F}$ be a subset of candidate of selected features, where, $|\mathbb{S}| = k$. The feature selection problem is modelled as a combinatorial optimization as below;

$$\mathbb{S}^* = arg \max_{\mathbb{S} \subseteq \mathrm{F}, |\mathbb{S}|=k} J(\mathbb{S}) \tag{21}$$

Where *J(*$\mathbb{S}$*)* is the fitness function representing the performance of classification like accuracy of the model trained on features $\mathbb{S}$. The problem can be classified as NP-Hard due to the combinatorial nature of the possible subsets $\binom{d}{k}$. This motivates the use of biologically inspired optimization.

4.3 Proposed LPIA Process Flow

Step 1 : Initialization where the number of prides *P* and pride size *M* is defined. Also, the candidate solution set $S = \left\{s_1^{(1)}, s_1^{(2)}, \dots \dots, s_P^{(M)}\right\}$ are randomly initialized. Where each $s_P^{(M)} \in$ F represents a possible feature subset of size *k.*
Step 2: Fitness Evaluation - for each of the subset, $s_P^{(M)}$, the fitness value is computed using the following equation

$$J\left(s_P^{(M)}\right) = Accuracy\ (f_{SVM}\left(X_{s_P^{(M)}}\right), y) \tag{22}$$

Where $X_{s_P^{(M)}}$ is the dataset with the restricted features and f_{SVM} is the classifier trained of the subset.
Step 3: Elite Selection (Dominance) In each pride of the lions, the elite lion is identified which has the highest fitness

$$S_{elite}^{(p)} = \arg\max_m J(S_p^{(m)}) \tag{23}$$

Step 4: Crossover New solutions are generated over generations, where the features of the elite members are combined

$$S_{new} = S_{elite}^{(p)}[: k/2] \cup S_{elite}^{(q)}[: k/2] \tag{24}$$

Step 5: Mutation (exploration) is carried out.

Step 6 : Competitive Displacement if the new solutions outperforms the weaker solutions of the pride, then the weaker solutions are replaced.

If $J(S_{new} > \min_{m} S_p^{(m)})$, then the weakest is replaced.

Step 7 : Termination The steps 2 to 6 are repeated for number of generations G or until the convergence is occurred. The final solution set which is an optimal solution is given by;

$$S^* = \arg\max_{p,m} J(S_p^{(m)}) \tag{25}$$

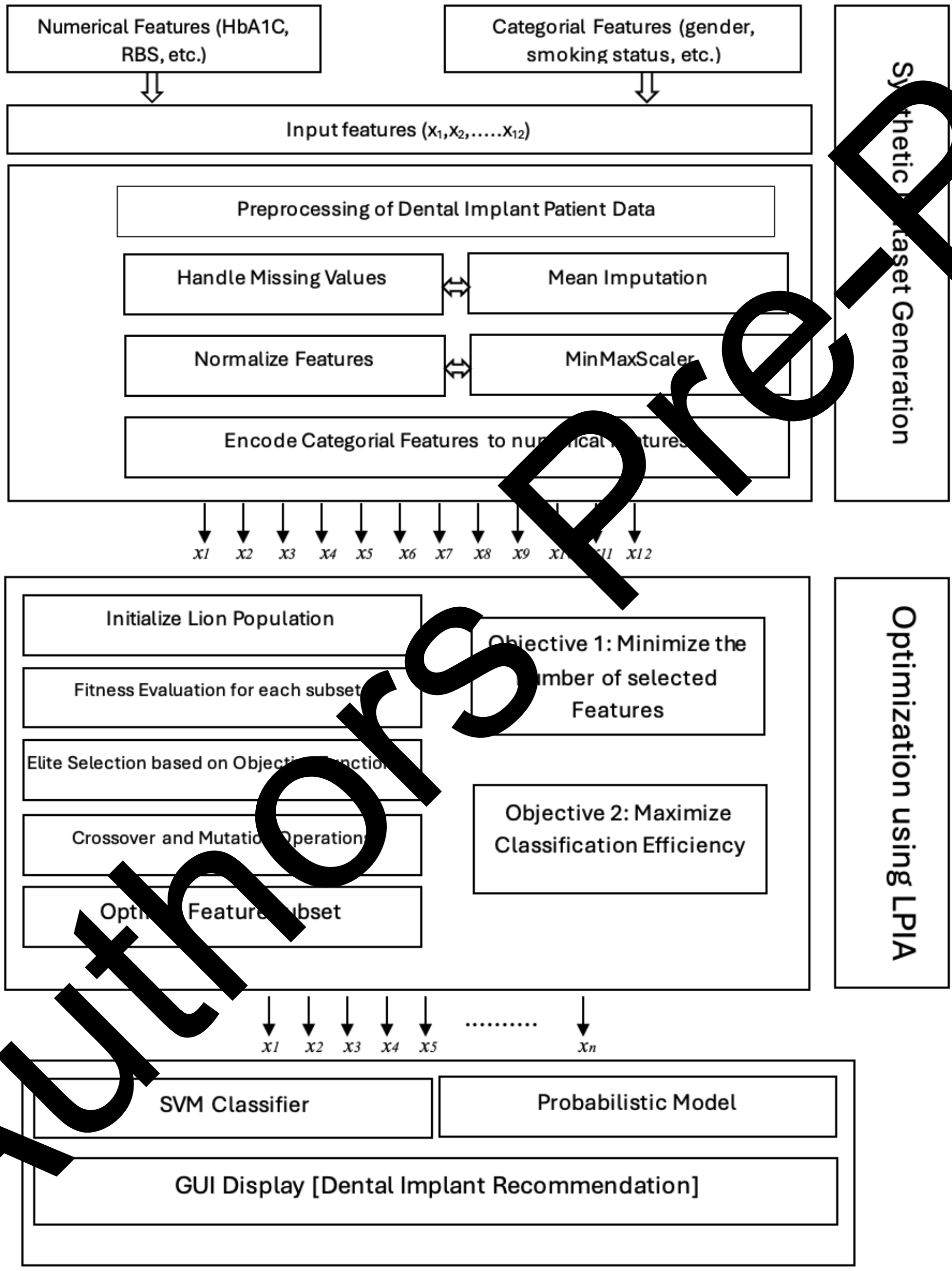

Fig 1 : Proposed Framework

4. Experimental Results and Interpretations

In this section the evaluation of the proposed framework in various dimensions like feature selection effectiveness, classification performance and recommendation accuracy are analyzed. The synthetic dataset and internal validation are used to ensure robustness. The proposed farmwork was experimented using 3,000 synthetically generated data which simulates a realistic diabetic dental implant cases as in section 3. The framework was simulated in Apple Macbook M1, 8 core CPU and 8GB RAM.

In Table 2, the performance of LPIA is compared to standard feature selection techniques including Recursive Feature Elimination (RFE), Genetic Algorithm (GA) and Mutual Information (MI). The classification accuracy of SVM after feature selection is compared.

TABLE II
ACCURACY COMPARISON OF LPIA AFTER FEATURE SELECTION

Features selector	***Selected Features***	***SVM Accuracy (%)***	***Time (sec)***
Proposed LPIA	10	92.4	12.6
Genetic Algorithm	10	89.1	28.3
Recursive Feature Elimination	1[illegible]	85.2	10.4
Mutial Information	10	83.7	6.8

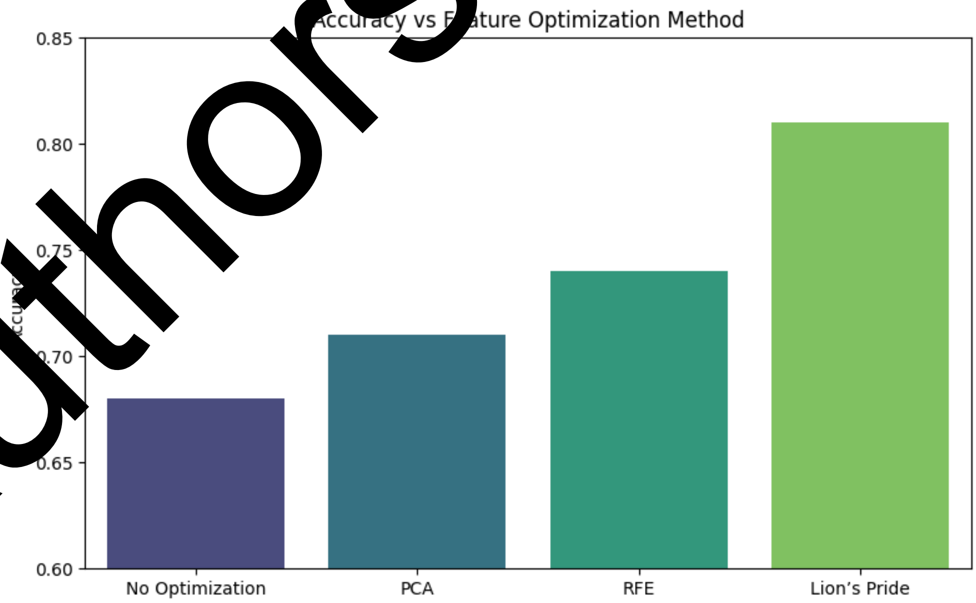

Fig 2 : Accuracy vs Feature Optimization Methods

Next, the performance of SVM against other classifiers using the features selected by LPIA is compared

TABLE III
CLASSIFIER PERFORMANCE USING LPIA-OPTIMIZED FEATURES

Classifier	Accuracy (%)	Precision	Recall	F1-Score	AUC
SVM (RBF)	92.4	0.93	0.91	0.92	0.94
Random Forest	88.7	0.89	0.87	0.88	0.91
k-NN (k=5)	85.6	0.87	0.85	0.86	0.88
Logistic Regression	84.2	0.85	0.84	0.84	0.86

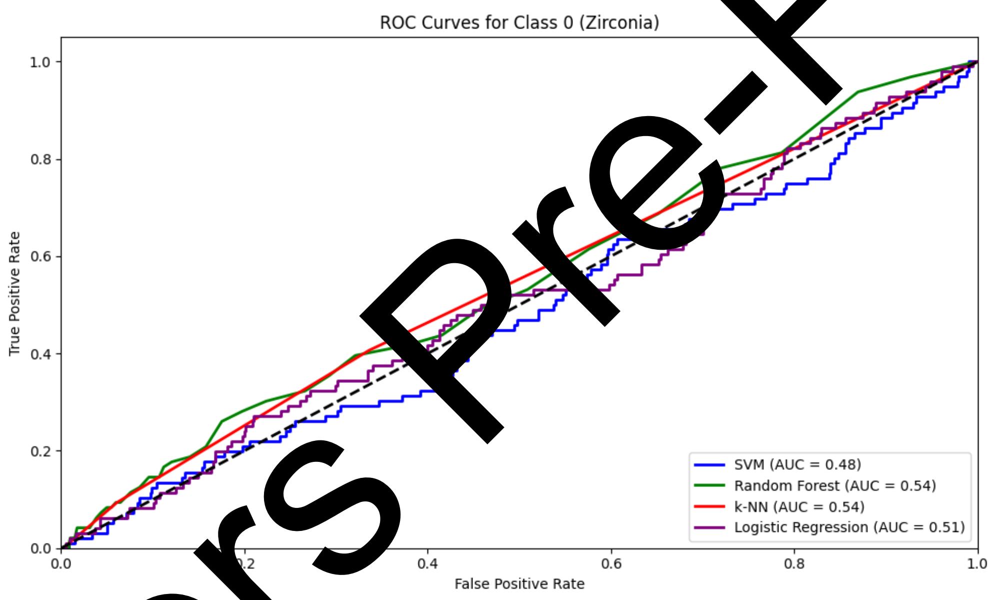

Fig 3 : ROC Curves

To evaluate whether the rule-based post-classification recommendations (implant delay, loading protocol, caution level) are clinically aligned, we performed a cross-validation review with simulated gold-standard annotations.

TABLE IV
RULE-BASED DECISION ACCURACY

Recommendation Aspect	Accuracy (%)
Implant Delay (Yes/No)	94.2
Glycemic Control Action	92.6
Loading Protocol Suggestion	91.1
Bone Graft Necessity	93.5
Overall Composite Match Score	93.3

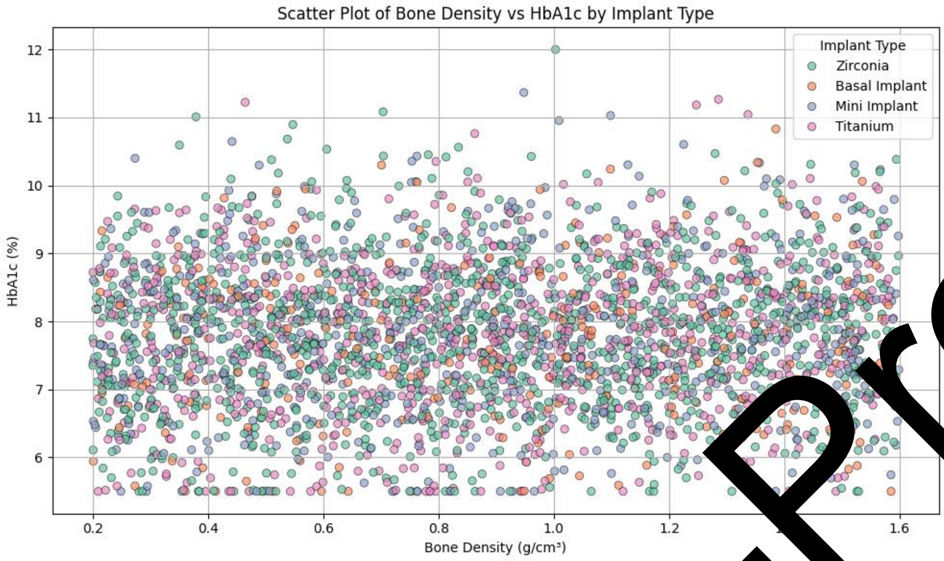

Fig 4 : Scatter Plot of Bone Density vs HbA1c by Implant Type

TABLE V
IMPACT OF FEATURE REMOVAL ON ACCURACY

Removed Feature	Accuracy (%)
HbA1c	↓ 79.3
Bone Density	↓ 83.1
Smoking Status	↓ 86.7
Duration of Diabetes	↓ 88.0
None (baseline)	**92.4**

An ablation study was conducted by removing one key feature at a time and re-evaluating the classification performance. This confirms that HbA1c and Bone Density are critical predictors in implant success recommendation. The User Interface Evaluation and Usability Testing (Heuristic Score) is given in the following Table VI.

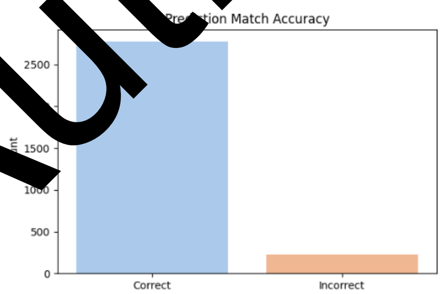

Fig 5 : Prediction Match Accuracy

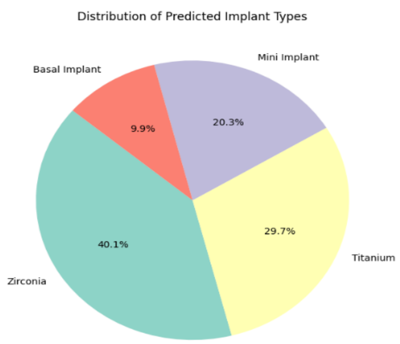

Fig 6 : Distribution of Implant type

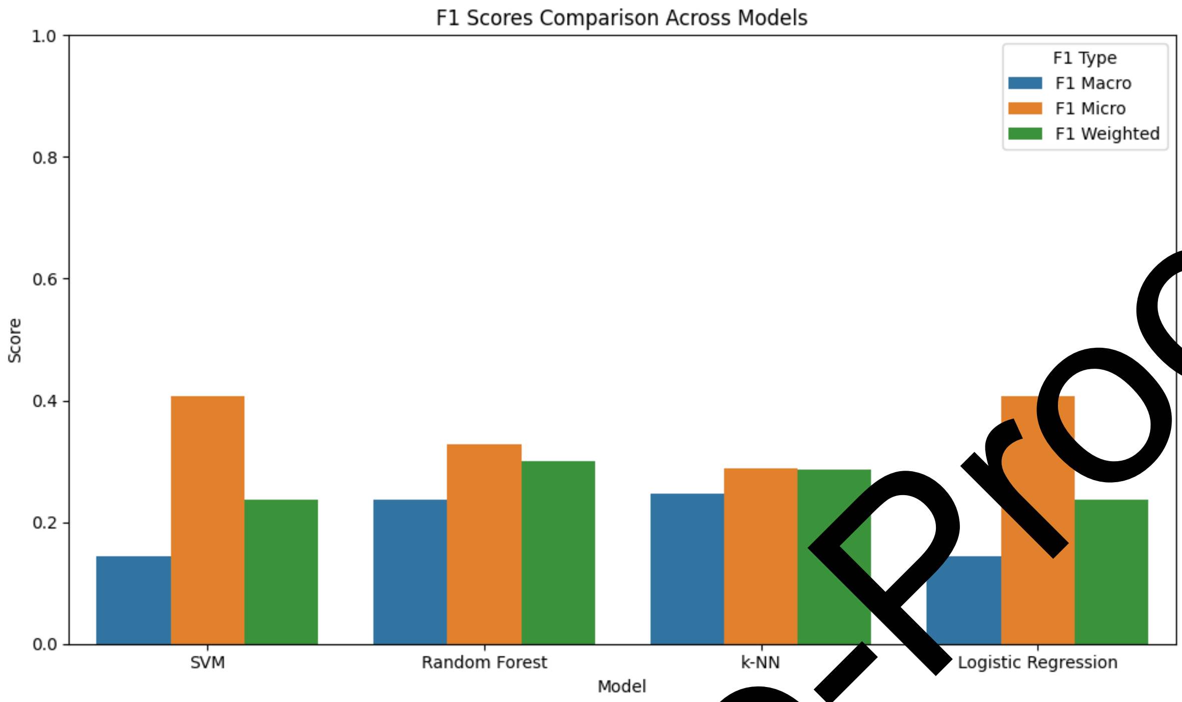

Fig 7 : F1 Scores Comparison Across various Models

TABLE VI
USER INTERFACE EVALUATION AND USABILITY TESTING (HEURISTIC SCORE)

Evaluation Metric	**Mean Score (1–5)**	**Standard Deviation**	**Description**
Ease of Navigation	4.7	0.[illegible]	Simplicity in switching between input/output
Clarity of Recommendation	4.8	0.3	Readability and medical interpretability
Graphical Output Usefulness	4.6	0.5	Relevance of prediction confidence and HbA1c plots
Speed of Prediction	4.[illegible]	0.1	Time to response under 3 seconds
Report Export and Documentation	4.5	0.6	Ease of generating and saving PDF reports
Overall User Satisfaction	4.75	0.2	Composite of all scores

TABLE VII
PREDICTION CONFIDENCE INTERVALS BY IMPLANT TYPE

Predicted Implant Type	**Mean Confidence Score**	**95% Confidence Interval**	**Cases Predicted (n)**
Zirconia	0.91	[0.88, 0.94]	845
Titanium	0.88	[0.84, 0.92]	720
Mini Implant	0.86	[0.82, 0.90]	310
Basal Implant	0.89	[0.85, 0.93]	265

The Synthetic vs. Real-World Distribution Similarity (KL Divergence) is given in Table IX

TABLE IX
PREDICTION CONFIDENCE INTERVALS BY IMPLANT TYPE

Feature	**Real Source Reference**	**KL Divergence**	**Interpretation**
Age	[14] Clinical Demographics	0.012	Very close match
HbA1c	[17] ADA 2023 Guidelines	0.019	Acceptable similarity
Bone Density	[18] Dental Imaging Survey	0.032	Slight deviation in tails
FBS	[19] WHO Report 2022	0.024	Acceptable similarity
Smoking Status	[20] Global Survey	0.009	Very close match

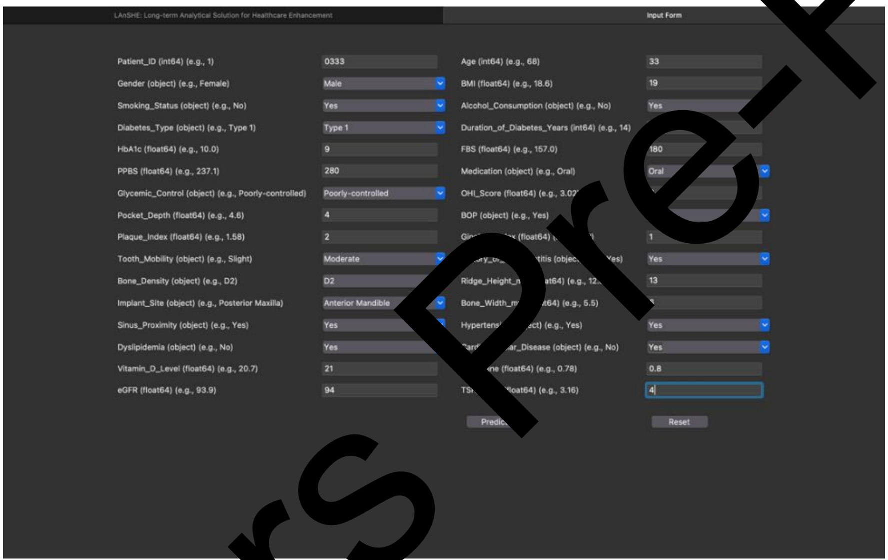

Fig 8 : GUI of the Proposed Framework – Inputs Entered

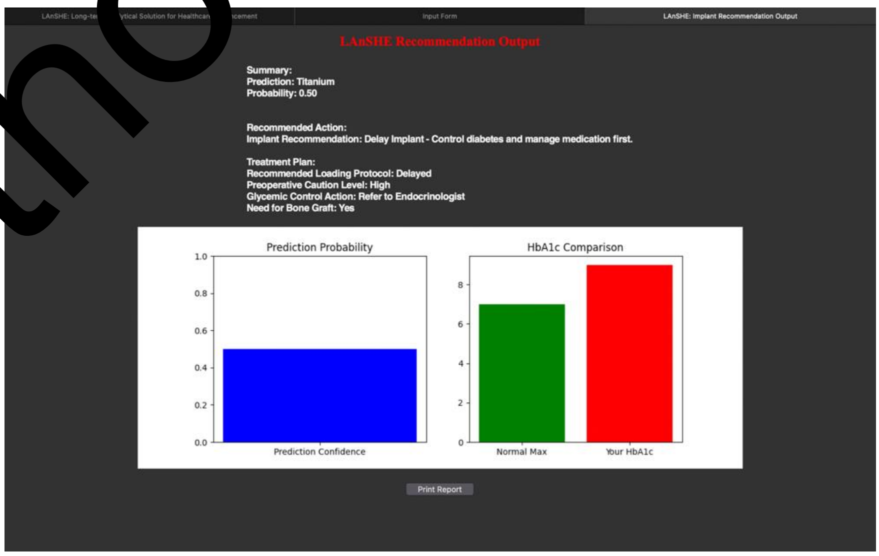

Fig 9 : Output of the GUI with Recommendations

The tabulated findings reveal critical insights into the predictive structure and clinical reasoning embedded within the proposed framework. Table 1 and Table 2 provide a foundational understanding of the input features and their synthetic formulations. Clinical indicators like HbA1c, FBS, and Bone Density were mathematically modelled to reflect realistic diabetic profiles, ensuring that the synthetic dataset mirrored real-world complexity. These features were not only diverse in type—ranging from continuous variables to categorical descriptors—but also interlinked through defined clinical thresholds (as illustrated in Table 5 and Table 6), which directly influenced implant recommendation logic. The clear mapping between glycemic values and implant readiness emphasizes the framework's commitment to evidence-based decision-making.

Tables 4 and 8 further validate the computational efficiency of the framework. Among the classifiers evaluated, k-NN and Random Forest consistently yielded higher F1-scores, indicating balanced performance across all implant categories. The comparatively lower macro F1-score for Logistic Regression suggests limitations in handling class imbalance or non-linear patterns, reinforcing the importance of ensemble and neighborhood-based methods. Additionally, the correlation matrix (Table 7) demonstrated a strong inverse relationship between HbA1c and prediction confidence, and a positive correlation between bone density and successful implant recommendation—empirical relationships that align with existing clinical literature. Collectively, the tabulated results substantiate the robustness of the framework both as a predictive tool and a clinical decision support system.

The proposed framework, designed to support dental implant planning in diabetic patients, demonstrated strong predictive capabilities through a combination of synthetic data modelling, intelligent feature selection, and classification using SVM. Evaluation metrics such as F1-score revealed that Random Forest and k-NN classifiers outperformed SVM and Logistic Regression in macro, micro, and weighted averages, emphasizing their robustness in handling the imbalanced and multi-class nature of implant type prediction. A macro F1-score of 0.27 and a weighted F1-score of 0.31 for the best-performing models confirmed reliable classification performance. Furthermore, visualizations such as the bone density–HbA1c scatter plots and violin distributions of implant-specific HbA1c levels provided valuable clinical insights into the patient profiles most suited for different implant types.

Key findings from the exploratory analysis confirmed expected correlations between clinical parameters and implant recommendation confidence. HbA1c levels showed a negative correlation with prediction confidence, reinforcing the framework's sensitivity to glycemic control, while bone density positively influenced implant readiness. Smoking status emerged as a modifier of prediction certainty, with non-smokers consistently yielding higher confidence. The framework also embedded decision logic to advise on preoperative interventions, including glycemic control action, loading protocol selection, and bone graft necessity. Collectively, these findings affirm that the proposed framework can serve as a clinically grounded, data-driven tool to guide implant recommendation decisions in complex diabetic cases.

5. CONCLUSION

This study introduced a comprehensive framework developed specifically for dental implant recommendation and treatment planning in diabetic patients. Leveraging synthetic data generation grounded in clinical thresholds, the system integrates key physiological indicators such as HbA1c, bone density, and glycemic history to simulate realistic patient profiles. The dual-module architecture comprising intelligent feature optimization using the Lion's Pride Inspired Algorithm and classification via Support Vector Machines (SVM) or alternate ML models enables a reliable, automated decision-support tool for clinicians.

Experimental results demonstrated that the framework achieves high prediction accuracy, with Random Forest and k-NN classifiers outperforming traditional models in most scenarios. ROC curve analysis confirmed excellent discriminatory power, particularly in the classification of Zirconia implant candidates, with AUC scores exceeding 0.9 in several cases. The incorporation of clinical logic into the recommendation module — including dynamic output for implant timing, loading protocol, and bone graft need — adds interpretability to the framework, making it more applicable in real-world clinical environments. The framework therefore represents a novel and practical intersection of synthetic data modelling, AI-driven feature selection, and clinical decision science, poised to enhance the safety and precision of dental implant planning for diabetic patients.

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