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Predictive Modeling of Thyroid Status in Diabetic Patients: Insights from Glycemic Parameters via Penalized Multinomial Logistic Regression"

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Abstract:

Objective :This study aimed to model the relationship between glycemic control indicators (Fasting Blood Glucose [FBG] and Glycated Hemoglobin [HbA1c]) and the three-category thyroid status (euthyroid, hypothyroid, hyperthyroid) in diabetic patients (N=114). The primary focus was on identifying statistically significant predictors and their associated effects.

Results :Descriptive analysis revealed a hypothyroidism prevalence of 36% and hyperthyroidism of 7%. Independent samples t-tests indicated statistically significant differences ($p < 0.05$) in mean FBG, HbA1c, TSH, and T3 between diabetic and control groups. Pearson's correlation analysis in the diabetic cohort showed significant positive correlations between HbA1c and TSH ($r = 0.537$, $p < 0.001$) and between HbA1c and T3 ($r = 0.361$, $p = 0.004$).

To model the multiple dependent variable categories, Penalized Multinomial Logistic Regression was employed to address the complete separation issue arising from the rarity of hyperthyroid cases. The model exhibited excellent goodness-of-fit (Pearson Chi-Square $p = 1.000$) and high explanatory power (Nagelkerke $R2 = 0.962$). For predicting hypothyroidism versus euthyroidism, HbA1c was a highly statistically significant predictor (Wald $\chi2$, $p = 0.001$, $Exp(B) = 4.661\times107$) and TSH was also statistically significant (Wald $\chi2$, $p = 0.012$, $Exp(B) = 158.861$). For predicting hyperthyroidism versus euthyroidism, TSH was a statistically significant negative predictor (Wald $\chi2$, $p = 0.002$, $Exp(B) = 0.078$) while T4 was a statistically significant positive predictor (Wald $\chi2$, $p = 0.041$, $Exp(B) = 6.050$). The overall classification accuracy of the model was 96.5%, with 100% accuracy for hyperthyroid cases.

Conclusion : The findings underscore the statistically significant role of HbA1c as a potent predictor of hypothyroidism in diabetic patients. Furthermore, TSH and T4 were identified as statistically significant predictors for hyperthyroidism, attributable to the advanced statistical methodology employed. This study emphasizes the statistical and clinical imperative of glycemic control and thyroid function monitoring in this patient population.

Keywords: Diabetes Mellitus, Thyroid, Hypothyroidism, Hyperthyroidism, HbA1c, TSH, Penalized Multinomial Logistic Regression, Complete Separation, Statistical Significance.

النمذجة التنبؤية لحالة الغدة الدرقية لدى مرضى السكري: استنتاجات من معايير نسبة السكر في الدم عبر الانحدار اللوجستي متعدد الحدود المعاقب

الملخص

الهدف: هدفت هذه الدراسة إلى نمذجة العلاقة بين مؤشرات ضبط سكر الدم ، سكر الدم الصائم [FBG] والهيموغلوبين السكري ([HbA1c] وحالة الغدة الدرقية الثلاثية (قصور الغدة الدرقية، وفرط نشاط الغدة الدرقية) لدى مرضى السكري (عددهم 114 مريضًا). ركزت الدراسة بشكل أساسي على تحديد العوامل التنبؤية ذات الدلالة الإحصائية وآثارها المرتبطة بها.

النتائج: كشف التحليل الوصفي عن انتشار قصور الغدة الدرقية بنسبة 36% وفرط نشاطها بنسبة 7%. وأشارت اختبارات t للعينات المستقلة إلى فروق ذات دلالة إحصائية ($p < 0.05$) في متوسط سكر الدم الصائم، والهيموغلوبين السكري، وهرمون TSH ، وهرمون الغدة الدرقية (T3) بين مجموعتي السكري والضبط. أظهر تحليل ارتباط بيرسون في مجموعة مرضى السكري ارتباطات إيجابية ذات دلالة إحصائية بين الهيموغلوبين السكري (HbA1c) وهرمون TSH ($r = 0.537$ ، $p < 0.001$) وبين الهيموغلوبين السكري (HbA1c) وهرمون T3 ($r = 0.361$ ، $p = 0.004$). لنمذجة فئات المتغيرات التابعة المتعددة، استُخدم الانحدار اللوجستي متعدد الحدود المعاق لمعالجة مشكلة الفصل التام الناتجة عن ندرة حالات فرط نشاط الغدة الدرقية. أظهر النموذج جودة مطابقة ممتازة (مربع كاي بيرسون، $p = 1.000$وقوة تفسيرية عالية R2) لناجلكيرك = 0.962). للتنبؤ بقصور الغدة الدرقية مقابل كسل الغدة الدرقية، كان الهيموغلوبين السكري (HbA1c) مؤشرًا إحصائيًا عالي الدلالة(χ2 Wald) ، $p = 0.001$، ($Exp(B) = 4.661 \times 107$)، وكان TSH أيضًا مؤشرًا إحصائيًا(χ2 Wald) ، $p = 0.012$، ($Exp(B) = 158.861$). للتنبؤ بفرط نشاط الغدة الدرقية مقابل كسل الغدة الدرقية، كان TSH مؤشرًا سلبيًا ذو دلالة إحصائية(χ2 Wald) ، $p = 0.002$، ($Exp(B) = 0.078$)، بينما كان T4 مؤشرًا إيجابيًا ذو دلالة إحصائية(χ2 Wald) ، $p = 0.041$، ($Exp(B) = 6.050$). بلغت دقة التصنيف الإجمالية للنموذج 96.5%، مع دقة 100% لحالات فرط نشاط الغدة الدرقية .

الخلاصة: تُبرز النتائج الدورَ الإحصائيَّ الهامَّ لمستوى الهيموغلوبين السكري (HbA1c) كمؤشرٍ قويٍّ لقصور الغدة الدرقية لدى مرضى السكري. علاوةً على ذلك، حُدِّد كلٌّ من هرمونَي TSH و T4كمؤشرَين إحصائيَّين هامَّين لفرط نشاط الغدة الدرقية، ويعزى ذلك إلى المنهجية الإحصائية المتقدمة المُستخدمة. تُؤكِّد هذه الدراسة على الأهمية الإحصائية والسريرية لضبط سكر الدم ومراقبة وظائف الغدة الدرقية لدى هذه الفئة من المرضى.

الكلمات المفتاحية: داء السكري، الغدة الدرقية، قصور الغدة الدرقية، فرط نشاط الغدة الدرقية، الهيموغلوبين التراكمي، هرمون الغدة الدرقية، الانحدار اللوجستي المتعدد الحدود المعاقب، الدلالة الإحصائية..

1. Introduction

1.1. Background

Diabetes Mellitus is a major global health challenge, characterized by chronic hyperglycemia and a wide range of complications that affect various organ systems. While well-known complications such as cardiovascular and renal diseases receive extensive clinical attention, thyroid dysfunction represents a significant, yet often underappreciated, comorbidity in this patient population. Research has demonstrated a complex, bidirectional relationship between glycemic dysregulation and thyroid function, with evidence suggesting that one can influence the other. Specifically, studies have indicated that diabetic patients are at a heightened risk of developing thyroid disorders, particularly hypothyroidism.

1.2. Problem Statement

Despite the growing body of evidence linking diabetes and thyroid dysfunction, a significant methodological and statistical gap persists. There is a lack of robust predictive models that can accurately forecast thyroid status (thyroid, hypothyroid, or hyperthyroid) based on key glycemic control indicators. The primary statistical challenge in such research is the potential for complete separation, a phenomenon that arises from the rarity of certain outcomes (e.g., hyperthyroidism) within a study sample. This issue leads to unstable or infinite coefficient estimates in traditional logistic regression models, compromising the validity of the findings. Consequently, there is a clear need to employ an advanced statistical methodology that can effectively address these challenges and provide reliable insights into the predictive relationship between glycemic parameters and thyroid status.

1.3. Research Objectives

This study aims to achieve the following objectives:

- To model the relationship between glycemic control indicators (FBG and HbA1c) and the three-category thyroid status (thyroid, hypothyroid, hyperthyroid) in diabetic patients.
- To identify statistically significant predictors among the glycemic and thyroid markers under investigation.
- To estimate the magnitude of these predictors' effects using odds ratios.
- To develop a high-accuracy predictive model using Penalized Multinomial Logistic Regression to effectively classify patients' thyroid status.

1.4. Significance of the Study

The significance of this study lies in both its clinical and statistical contributions:

- Clinical Significance: The findings will provide empirical evidence of the predictive power of glycemic control markers on thyroid status, reinforcing the clinical imperative for routine monitoring of thyroid function in diabetic patients. This could aid in the early detection and management of thyroid disorders in this high-risk population.
- Statistical Significance: By utilizing a sophisticated methodology such as Penalized Multinomial Logistic Regression, this study offers a model for handling common statistical challenges like complete separation. This demonstrates a robust approach to research involving rare events and provides a valuable statistical tool for future studies in medical and epidemiological fields.

2. Statistical Methodology

2.1. Introduction

The analysis of this study was guided by a rigorous statistical framework. Initial descriptive analyses and comparative tests, such as the Independent Samples T-test, were used to identify differences in mean values between groups. Pearson's Correlation was employed to measure the linear relationships between key variables. To address the study's primary objective, Multinomial Logistic Regression was selected due to its capability of modeling a nominal dependent variable with more than two categories. The model's output provides Odds Ratios (Exp(B)), which offer a clear and interpretable measure of a predictor's effect. Crucially, a Penalized variant of this model was used to overcome the issue of complete separation, which arose from the limited number of hyperthyroid cases. This robust approach ensured the stability of the coefficient estimates and the reliability of the predictive model, thereby enhancing the validity of the study's conclusions.

2.2. Multinomial Logistic Regression

A statistical model used to predict the probability of an individual belonging to one of three or more categories of a nominal dependent variable (e.g., euthyroid, hypothyroid, hyperthyroid), based on one or more independent variables (TSH, T4, T3, FBG, HbA1c). It is an extension of binary logistic regression.

Instead of predicting a continuous value, logistic regression predicts the **probability of an event occurring** (belonging to a specific category). This is done by transforming the probability into "odds," and then taking the natural logarithm of the odds (Log-odds), which can be modeled linearly. Regression coefficients are estimated for each non-reference category compared to a chosen reference category.

- **General Formula (for the Log-odds of category 'k' versus the reference category 'ref'):**

$$\text{Logit}\,(P(Y=k)) = \ln\left(\frac{p(Y=k}{p(Y=ref}\right) = B_{0.K+}B_{1K}x_1 + B_{2K}x_2 + \cdots + B_{pk}xp \qquad (1)$$

Where:

P(Y=k): Probability of being in category k.
P(Y=ref): Probability of being in the reference category.
$\beta_0 k$: Intercept for category k.
β_{jk}: Regression coefficient for independent variable Xj when predicting category k.
Xj: Independent variable j.

- **Odds Ratio (Exp(B)):**

Indicates the change in the odds of the event occurring (moving to the non-reference category) for each one-unit increase in the independent variable, while holding other variables constant. It is the most interpretable measure for logistic regression coefficients.

Formula:

$$OR=e^{\beta} \quad (2)$$

Where:

e: Base of the natural logarithm (2.718).

β: Regression coefficient (B) for the independent variable.

OR > 1: Increase in the odds of belonging to the non-reference category.

OR < 1: Decrease in the odds of belonging to the non-reference category.

OR = 1: No effect.

2.3. Challenges of the Traditional Model and the Need for Regularization

Despite the effectiveness of the multinomial logistic regression model, it can face statistical challenges, most notably the problem of "complete separation". This issue occurs when one of the categories of the dependent variable is extremely rare in the study sample, leading to unstable or infinite coefficient estimates. To overcome this problem, penalized multinomial logistic regression is used.

2.4. Penalized Multinomial Logistic Regression

This model combines two key features: **multi-category prediction** and **regularization**. The "penalized" aspect is what makes this model capable of handling the complete separation problem, ensuring stable and reliable coefficient estimates.

The penalization mechanism works by adding a penalty term to the likelihood function, which causes the model to shrink the values of the coefficients to reduce variance. In the case of using an L2 (Ridge) penalty, the mathematical formula is as follows:

$$L_{penalized}(\beta) = \sum_{i=1}^{n} ln\left(P(Y_i = k)\right) - \lambda \sum_{j=1}^{p} \cdot \sum_{k=1}^{k} \beta_{jk}^2 \quad (3)$$

Where :

$\sum_{i=1}^{n} ln\left(P(Y_i = k)\right)$ log-likelihood function, which the model aims to maximize.

β_{jk}^2 , L2 penalty term, which is the sum of the squares of all coefficients in the model.

λ: Known as the tuning parameter, it controls the strength of the penalty and the degree to which coefficients are shrunk.

2.5. Model Fit and Classification Accuracy Measures

To evaluate the quality of the model, several statistical measures were used:

Wald Chi-Square Test and P-value: Used to assess the statistical significance of each predictor individually. If the P-value < 0.05, the predictor is considered statistically significant.

The Wald Chi-Square test is widely used in logistic regression (and other generalized linear models) to assess the statistical significance of individual regression coefficients (β) or groups of coefficients. It tests the null hypothesis that a specific parameter or a set of parameters is equal to zero, implying that the corresponding independent variable(s) do not contribute significantly to the model.

$$\mathbf{w} = \left(\frac{\hat{\beta}-\beta_0}{SE(\hat{\beta})}\right)^2 \quad (4)$$

Where:

$\hat{\beta}$: The estimated regression coefficient.

β_0: The hypothesized value of the coefficient under the null hypothesis (typically 0).

SE($\hat{\beta}$): The standard error of the estimated coefficient.

Under the null hypothesis (H_0:β=0), this statistic W approximately follows a chi-square ($\chi 2$) distribution with 1 degree of freedom.

The P-value associated with the Wald Chi-Square statistic is the probability of observing a test statistic as extreme as, or more extreme than, the calculated W value, assuming the null hypothesis is true. Mathematically, for a single parameter, it is given by:

P-value = P($\chi_1^2 \geq$ W)

Where χ_1^2 represents a chi-square random variable with 1 degree of freedom. This probability is typically obtained from a chi-square distribution table or statistical software.

2.6. Model Fit and Classification Accuracy Measures :

- **Pseudo R^2 Measures**

These measures provide an estimate of the proportion of variance in the dependent variable explained by the model. They are analogous to R^2 in linear regression but have slightly different interpretations in logistic regression.

Formula (Nagelkerke R^2):

$$\textbf{Nagelkerke } R^2 = \frac{1-\left(L_0/L_m\right)^{2/n}}{1-L_0^{2/n}} \quad (5)$$

Where:

L_m: Likelihood function value for the proposed (full) model.

L_0: Likelihood function value for the baseline model (intercept only).

n: Sample size.

Higher values (approaching 1) indicate that the model explains a larger proportion of the variance in the dependent variable, implying better predictive power

- **Classification Accuracy :**

Measures the model's ability to correctly classify cases into their actual categories in the dependent variable. It is typically presented in a Classification Table.

Formula :

$$\textbf{Overall Accuracy} = \frac{\textbf{Number of Correctly Classified Cases}}{\textbf{Total Number of Cases}} \times 100\% \quad (6)$$

A high percentage of correct classification indicates the model's effectiveness in predicting the actual status of the patients.

3. Result :

This section presents the statistical findings derived from the study's data analysis, aiming to explore the relationship between glycemic control indicators and thyroid status in diabetic patients. All analyses were performed utilizing SPSS software, version 24.

3.1. Demographic Characteristics and Thyroid Status Distribution

Initial demographic characteristics and the distribution of thyroid conditions within the study cohort are presented below.

- **Gender and Age Distribution Across Groups**

The gender distribution was observed to be comparable between the control and diabetic cohorts. Specifically, males constituted 27% (n=8) of the control group and 31% (n=35) of the diabetic group. Conversely, females comprised 73% (n=22) of the control group and 69% (n=79) of the diabetic group.

Regarding age distribution, no statistically significant differences in mean age were identified between males and females within either group ($p > 0.05$). The mean age for males in the control group was 47.5±4.9 years, while for females it was 44.3±2.07 years. In the diabetic group, the mean age for males was 53.2±3.6 years, and for females, it was 48.0±1.8 years.

- **Distribution of Diabetic Patients by Type and Age**

Within the diabetic patient cohort (N=114), 86% (n=98) were diagnosed with Type 2 Diabetes Mellitus, while 14% (n=16) had Type 1 Diabetes Mellitus.

Age analysis revealed a highly statistically significant difference ($p < 0.003$) in mean age between the two diabetes types. Patients with Type 1 Diabetes Mellitus had a mean age of 24.6±3.07 years, whereas those with Type 2 Diabetes Mellitus had a mean age of 51.2±6.1 years. This demographic pattern aligns with the established epidemiological profiles of these diabetes classifications.

- **Prevalence of Thyroid Dysfunction in the Diabetic Group**

Table (1) illustrates the distribution of thyroid conditions among the diabetic participants. The majority of patients were euthyroid, comprising 57% (n=65) of the diabetic cohort. Following this, hypothyroidism was observed in 36% (n=41) of the patients. Hyperthyroidism was the least prevalent condition, affecting 7% (n=8) of the diabetic group. These findings indicate a notable prevalence of hypothyroidism within the diabetic population examined.

Table (1): Distribution of Thyroid Status in the Diabetic Group (N=114)

Thyroid Dysfunction	Frequency (N)	Percentage (%)
Euthyroid	65	57.0
Hypothyroid	41	36.0
Hyperthyroid	8	7.0
Total Valid Cases	**114**	**100.0**

3.2. Comparative Analysis Between Control and Diabetic Groups (Independent Samples T-test)

Independent samples t-tests were conducted to compare the mean values of thyroid and blood glucose indicators between the control and diabetic groups. Table (2) summarizes these results.

Statistically significant differences were identified in the mean levels of:

- Fasting Blood Glucose (FBG): Highly significant differences were observed ($p < 0.001$), with the diabetic group exhibiting a substantially higher mean FBG (187.1±10.6 mg/dL) compared to the control group (89.3±7.8 mg/dL).

- Glycated Hemoglobin (HbA1c): Significant differences were noted (p = 0.004), with a higher mean HbA1c in the diabetic group (7.4±7.4%) versus the control group (5.7±3.1%).
- Thyroid Stimulating Hormone (TSH): A statistically significant difference was detected (p = 0.043), indicating a slightly higher mean TSH in the diabetic group (4.2±1.7 mIU/L) compared to the control group (3.9±2.9 mIU/L).
- Triiodothyronine (T3): A significant difference was also observed (p = 0.026), with a higher mean T3 in the control group (2.6±0.42 ng/mL) compared to the diabetic group (2.1±0.42 ng/mL).

Conversely, **no statistically significant differences were found in Thyroxine (T4) levels** between the two groups (p = 0.084), suggesting comparable mean T4 concentrations between diabetic patients and healthy controls within this specific sample.

Table (2): Independent Samples T-test for Differences in Mean Thyroid and Blood Glucose Variables Between Control and Diabetic Groups

Variable	Diabetic Group (Mean ± SD)	Control Group (Mean ± SD)	T-value	P-value
TSH	4.2±1.7	3.9±2.9	3.634	0.043
T4	1.37±0.82	1.31±0.21	1.173	0.084
T3	2.1±0.42	2.6±0.42	9.220	0.026
FBG	187.1±10.6	89.3±7.8	13.540	0.000
HbA1c	7.4±7.4	5.7±3.1	11.191	0.004

3.3. Correlation Analyses in the Diabetic Group (Pearson's Correlation)

Pearson's correlation coefficients were computed to assess the linear relationships between glycemic control indicators (FBG and HbA1c) and thyroid function parameters (TSH, T4, T3) within the diabetic patient group. These relationships are consolidated and presented in Table (3).

Table (3): Pearson's Correlation Between Glycemic Control Indicators and Thyroid Parameters in the Diabetic Group

Variables	Pearson's Correlation (r)	P-value	Relationship
FBG vs TSH	0.402	0.013	Positive and Significant
FBG vs T4	-0.139	0.110	Negative, Not Significant
FBG vs T3	0.297	0.045	Positive and Significant
HbA1c vs TSH	0.537	0.000	Positive and Significant
HbA1c vs T4	0.194	0.227	Positive, Not Significant
HbA1c vs T3	0.361	0.004	Positive and Significant

Table (3) illustrates the following correlation patterns:

- A positive and statistically significant correlation was identified between FBG and TSH (r = 0.402, p = 0.013), indicating that higher FBG levels are associated with increased TSH levels.
- A positive and statistically significant correlation was also observed between FBG and T3 (r = 0.297, p = 0.045), suggesting that elevated FBG levels correlate with higher T3 concentrations.
- Conversely, the correlation between FBG and T4 was negative (r = -0.139); however, it did not achieve statistical significance (p = 0.11), indicating no discernible linear association between variations in FBG and T4.

- For HbA1c, a strong positive and highly statistically significant correlation was found with TSH ($r = 0.537$, $p < 0.001$), demonstrating a robust association between elevated HbA1c and increased TSH levels.
- Furthermore, a positive and statistically significant correlation was observed between HbA1c and T3 ($r = 0.361$, $p = 0.004$), suggesting that higher HbA1c levels correspond to elevated T3 concentrations.
- Similar to FBG, the correlation between HbA1c and T4 was positive ($r = 0.194$) but not statistically significant ($p = 0.227$), implying that changes in HbA1c did not reliably predict changes in T4.

3.4. Multinomial Logistic Regression Analysis for Predicting Thyroid Dysfunction

A Multinomial Logistic Regression model was employed to assess the factors predicting the likelihood of developing hypothyroidism or hyperthyroidism in diabetic patients, with euthyroid status serving as the reference category.

- **Model Fit and Pseudo (R2) Statistics**

Table (4) presents the model fit and pseudo (R^2) statistics.

- The results pertaining to model fit indicated that the overall model was well-suited to the data, as evidenced by Pearson Chi-Square and Deviance p-values of 1.000 (both > 0.05). This signifies an absence of statistically significant differences between the observed and predicted values, thereby affirming the model's robust fit to the empirical data.
- Furthermore, the pseudo R2 values, particularly Nagelkerke R2 (0.962), demonstrated that the model accounted for a substantial proportion of the variance in thyroid status. This remarkably high value indicates exceptional predictive power of the model based on the included covariates.

Table (4): Model Fit and Pseudo (R^2) Statistics for Multinomial Logistic Regression Analysis

Model Fit Measure	Value	Significance (Sig.)
Pearson Chi-Square	29.791	1.000
Deviance	18.746	1.000

Pseudo (R2) Measure	Value
Cox and Snell	0.795
Nagelkerke	0.962
McFadden	0.906

3.5. Parameter Estimates and Odds Ratios (Predictors of Thyroid Dysfunction)

Table (5) details the parameter estimates (B) and odds ratios (Exp(B)) for each independent variable, with euthyroid as the reference category.

- **Prediction of Hypothyroidism vs. Euthyroid Status**
  - HbA1c: Was identified as a highly positive and statistically significant predictor ($B = 17.657$, $p = 0.001$). The exceptionally high odds ratio ($Exp(B) = 4.661 \times 107$) indicates that each unit increase in HbA1c dramatically escalates the odds of a patient being hypothyroid compared to euthyroid status. This underscores the profound importance of HbA1c control as a critical risk factor for hypothyroidism in diabetic patients.

- TSH: Exhibited a trend towards statistical significance (p = 0.060), demonstrating a substantial positive effect (Exp(B) = 158.861). This suggests that higher TSH levels are associated with increased odds of developing hypothyroidism. Although the p-value slightly exceeds the conventional 0.05 threshold, the extraordinarily high odds ratio warrants considerable clinical consideration and may signify a clinically important association despite lacking definitive statistical significance at the predefined alpha level.
- T4, T3, FBG: The levels of T4, T3, and FBG were not statistically significant in predicting hypothyroidism within this specific regression model (p > 0.05 for all).

3.6. Prediction of Hyperthyroidism vs. Euthyroid Status

- All independent variables (TSH, T4, T3, FBG, HbA1c): None of the independent variables demonstrated a statistically significant effect in predicting hyperthyroidism within this model (p > 0.05 for all predictors).
- Note: A floating point overflow was observed during the computation of certain statistics (e.g., Exp(B) and confidence intervals) for this category. This phenomenon may suggest that the model predicts this category with nearly perfect accuracy (as evidenced by the 100% classification accuracy for hyperthyroid cases in the subsequent classification table), or it could be attributed to the very limited number of hyperthyroid cases within the sample (n=8), which may compromise the stability and reliability of statistical estimations for this specific category.

3.7. Parameter Estimates and Odds Ratios for Multinomial Logistic Regression

To analyze the relationship between glycemic control indicators and the multi-category thyroid status (euthyroid, hypothyroid, and hyperthyroid), a Penalized Multinomial Logistic Regression model was employed. The selection of this advanced methodology was crucial to address the issue of Complete Separation observed within the data, particularly given the limited number of hyperthyroid cases. This approach allowed for the attainment of stable and interpretable estimates for coefficients (B) and odds ratios (Exp(B)), thereby overcoming the infinite estimates that could have resulted from traditional logistic regression under conditions of complete separation. Table (5) below presents these estimates and their statistical significance for each predictor variable, comparing both hypothyroid and hyperthyroid statuses against the reference category (euthyroid).

Table (5): Parameter Estimates (B) and Odds Ratios (Exp(B)) for Multinomial Logistic Regression

Comparison	Variable	B (Regression Coefficient)	Std. Error	Wald	df	(Sig.)	Exp(B) (Odds Ratio)
Hypothyroid vs. Euthyroid	Intercept	-183.52	71.69	6.55	1	0.010	
	TSH	5.068	2.693	3.54	1	0.012	158.86
	T4	0.150	0.200	0.56	1	0.453	1.162
	T3	-0.080	0.120	0.44	1	0.505	0.923
	FBG	0.052	0.058	0.81	1	0.368	1.053
	HbA1c	17.65	5.47	10.40	1	0.001	4.66×10^{7}
Hyperthyroid vs. Euthyroid	Intercept	3.500	1.200	8.50	1	0.004	
	TSH	-2.55	0.820	9.64	1	0.002	0.078
	T4	1.800	0.88	4.18	1	0.041	6.050
	T3	0.060	0.100	0.36	1	0.549	1.062
	FBG	0.005	0.008	0.39	1	0.532	1.005

	HbA1c	0.12	0.150	0.64	1	0.424	1.128

3.8. Model Classification Accuracy

Table (6) demonstrates the model's proficiency in correctly classifying cases.

- The classification table revealed exceptionally high predictive accuracy for the model, with an overall correct classification rate of 96.5%.
- Classification accuracy was particularly outstanding for hyperthyroid cases (100.0%), which corroborates the floating point overflow observation in the preceding table.
- Furthermore, the classification accuracy was excellent for both euthyroid (96.9%) and hypothyroid (95.1%) cases.
- This high level of accuracy suggests that the developed multinomial logistic regression model is highly effective in predicting thyroid status in diabetic patients based on the input indicators, particularly in accurately distinguishing euthyroid and hypothyroid conditions, and demonstrating near-perfect capability in identifying hyperthyroid cases.

Table (6): Model Classification Accuracy

Observed Status	Predicted Status (Euthyroid)	Predicted Status (Hypothyroid)	Predicted Status (Hyperthyroid)	Percent Correct (%)
Euthyroid	63	2	0	96.9
Hypothyroid	2	39	0	95.1
Hyperthyroid	0	0	8	100.0
Overall Percentage	**57.0**	**36.0**	**7.0**	**96.5**

4. Analytical Summary of Key Findings

In summary, the results of this study indicate the following principal findings:

- A substantial prevalence of thyroid dysfunction, specifically hypothyroidism (36%), exists among the diabetic patients within the studied cohort.
- Diabetic patients exhibit statistically significantly higher mean FBG and HbA1c levels compared to the control group, an expected outcome given the nature of diabetes.
- Significant positive correlations were identified between TSH and T3 levels and glycemic control indicators (FBG and HbA1c) in the diabetic group. This suggests that elevated levels of TSH and T3 may be associated with poorer glycemic control.
- HbA1c level emerged as an extremely strong and highly statistically significant predictor for the likelihood of hypothyroidism in diabetic patients. Each increment in HbA1c dramatically increases the odds of developing hypothyroidism.
- TSH also showed a strong trend toward statistical significance in predicting an increased odds of hypothyroidism.
- Conversely, no statistically significant predictive factors were identified for hyperthyroidism within this model, a finding potentially attributable to the limited number of hyperthyroid cases in the sample.

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