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Deciphering Pentraxin-3 and Interleukin-18: Leveraging Copious Section Algorithm for Classification in Early Detection and Severity Prognosis of Diabetic Foot Ulcers

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Abstract: In the Copious section algorithm we have classified into seven protocols such as Diabetic Forecast, Diabetic Synergetic Monitor, Diabetic Cardiac Symmetry ,Diabetic Hepa Profiler, Diabetic Life Pulse Analytics, and Diabetic Nephrite Profiler used to find diabetic foot ulcer wound healing percentage rate and also to compare the levels of Interleukin-18 (IL-18) and Pentraxin-3 (PTX-3) in separately with type 2 diabetes mellitus (T2DM) with or without foot ulcers (FUs) and also Its elevated levels have been reported in the blood of patients .This algorithm detect other physical issues which are associated and not associated to DFU(Diabetic Foot Ulcer).This algorithm acts as over all automated support system to patient .

Keywords: *Interleukin-18, Pentraxin-3(PTX-3), Diabetic Foot Ulcer and Copious section algorithm.*

1. Introduction

We have collected 50 blood samplesfrom the laboratory which include some samples from diabetic patients ,some constraints from normal persons . The study participants signed an informed consent form before the sample collection. We have also collected information like age, level of education, smoking status, diabetes in the family history, and clinical data. They questioned DFU patients mainly about skin issues, perfusion, nephropathy, and the existence of infections.

This sample analysis explains that 50 participants in that research in that category found 28 people suffering from T2DM with DIABETIC FOOT ULCER, 28 people with T2DM without DFU, and 22 healthy people. persons with T1DIABETIC MELLTIUS .Persons having wound in body or chronic disorder, or persons having infectious or chronic disorder, or who have heart diseases or liver disease or kidney disease or hepatitis. People said to be healthy people with normal blood pressure and non-smokers.

2. Sampleinformatics

Samples collected by clot activator tubes were used to draw venous blood samples from each participant after an overnight fast. The HbA1c test was conducted using EDTA tubes. Serum samples were then separated using a 4000 rpm motor for 10 minutes at room temperature. The serum samples that were intended to be analyzed for PTX-3 and IL-18 were carefully stored at -80 °C in order to be used later.

The samples for taken to classification and the classification are taken in clusters each cluster is taken as a binary input and the combination of all the cluster are structured.

The classification will give a combination of 128 output each combination will have a value associated with foot ulcer.

3. Demographic Tapestry analysis

The results show that T2DM patients with FU were slightly older than the other two groups (63.5 ± 6.0 vs.62.0 ± 6.7 respectively), and they were more

BMI: Body mass index*: The test included only the T2DM patients and T2DM patients with FU groups since the normal group was chosen to be non-smokers.

39.3%of T2DM with or without FUs were smokers or quit smoking compared to 60.7% for non-smokers. There was a significant difference between the study groups in terms of smoking status ($P < 0.05$), while there was no significant difference in BMI between the study groups ($P = 0.362$), as shown in Table 1.

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Table 2: Clinical characteristics of the study groups

	Normal (N=28)	T2DM (N=28)	T2DM with FU (N=28)	P value
Blood pressure				
Normal	28 (100%)	8 (28.6%)20 (71.4%)	16 (57.1%)	0.365#*
> 130 (mmHg)	0 (0%)	20 (71.4%)	12 (42.9%)	
Family history of DM				
Yes	18 (64.3%)	16 (57.1%)	17 (60.7%)	0.761#
No	10 (35.7%)	12 (42.9%)	11 (39.3%)	
Duration of diabetes (years)				
Mean (SD)	NA	7.2 (3.4)	8.2 (3.2)	0.260$
(Min, Max)	NA	(1.0, 13.0)	(4.0, 14.0)	
Median (Q1, Q3)	NA	7.0 (5.0, 9.2)	8.0 (5.8, 10.3)	

The Time period of diabetes in patients with FUs was slightly longer (8.2± 3.2 years) compared to T2DM patients without FUs (7.2 ± 3.4 years), but the difference was not statistically significant (P = 0.260).

Table3: Biochemical Disparities Across Study Cohorts

Parameter	Normal (N=28)	T2DM (N=28)	T2DM with FU (N=28)	P value	
				Overall	Post- hoc
HbA1c (%)					
Mean (SD)	4.7 (0.3)	8.0 (1.5)	9.8 (1.4)		<0.0001[a]
(Min, Max)	(5.2, 6.8)	(6.4, 12.2)	(7.8, 13.2)	<0.0001*	<0.0001[b]
Median (Q1, Q3)	5.7 (5.5, 5.9)	9.0 (7.9, 10.2)	9.6 (8.6, 10.5)		
FBG (mmol/L)					
Mean (SD)	5.3 (2.8)	11.3 (5.1)	11.2 (3.9)		0.0001[a]
(Min, Max)	(3.2, 13.9)	(3.6, 21.8)	(4.8, 21.4)	<0.0001*	<0.0001[b]
Median (Q1, Q3)	5.7 (4.2,6.2)	9.9 (6.7, 12.9)	10.9 (8.6, 13.7)		
Cholesterol (mmol/L)					
Mean (SD)	3.5 (0.9)	4.5 (1.0)	3.9 (0.7)		0.031[b]
(Min, Max)	(2.7, 6.1)	(2.9, 6.5)	(2.7, 5.3)	0.002#	0.002[c]
Median (Q1, Q3)	4.7 (3.8, 5.0)	5.0 (4.0, 5.4)	3.7 (3.4, 4.3)		
Triglycerides (mmol/L)					

ALT: Alanine transaminase; FBG: Fasting blood glucose; HbA1c: Hemoglobin A1c; HDL: high-density lipoprotein; LDL: Low-density lipoprotein. Significant P values (P < 0.05) are in bold. [a] Diabetic vs Controls; [b]T2DM with FU vs Controls &[c]T2DM vs T2DM with FU.

T2DM patients and T2DM patients with FUs had higher HbA1c and FBG than the normal other group , and these differences were (P 0.0001). Cholesterol and LDL values were lower in the T2DM patients with FUs group compared to the corresponding values for both T2DM patients without FUs and normal groups (P = 0.002 and

P= 0.001, respectively) creatinine and urea were significantly elevated in T2DM patients with FUs compared to the other two groups(P < 0.0001).

The next analysis is about classification if blood bio maker and these classification will provide a output with 128 classification with a high degree of accuracy

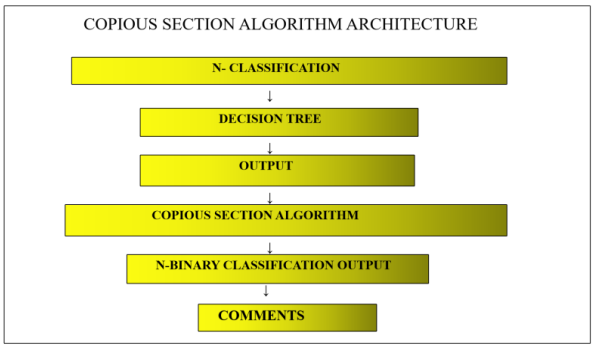
The classification based output is been determined and the output is designed for the compination of the clustures

Fig 1: CLASSIFICATION OF SEVEN BLOOD BIOMAKER

Diabetic Forecast	Diabetic Synergetic Monitor	Diabetic clarity Symmetry	Diabetic Cardiac Symmetry	Diabetic Hepa Profiler	Diabetic Life Pulse Analytics	Diabetic Nephro Profiler
Glucose Blood Pressure Insulin BMI Age Outcome	Pregnancies Glucose Skin Thickness Insulin Age Outcome	BUN ESR HB K Na WBC Lymph Neut PLT	BP Su Hemo HTN DM CAD Outcome classification	ALB ALP ALT AST BIL CHE CHOL CREA GGT PROT	BLDS tot_chole HDL_chole LDL_chole triglyceride hemoglobin urine_protein serum_creatinine SGOT_AST SGOT_ALT gamma_GTP SMK_stat_type_cd DRK_YN	Chest pain type Resting blood pressure cholestoral Fasting blood sugar Major vessels Thal Heart disease

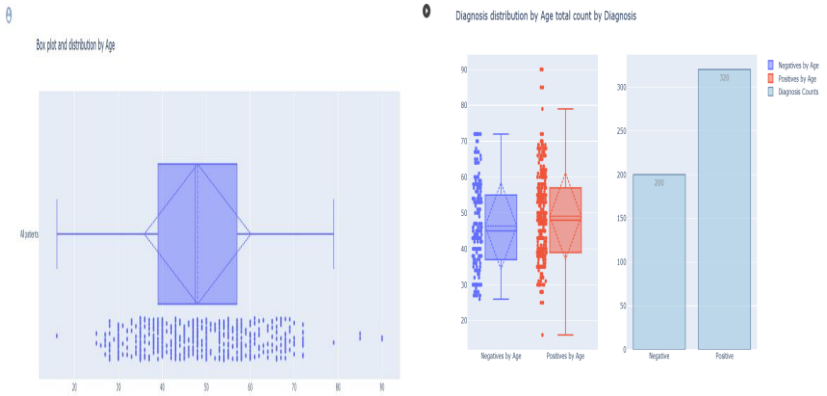
Seven classifications are taken such as Diabetic Forecast, Diabetic Synergetic Monitor, Diabetic Cardiac Symmetry, Diabetic Hepa Profiler, Diabetic Life Pulse Analytics, and Diabetic Nephro Profiler.

FIG 2: COPIOUS SECTION ALGORITHM ARCHITECTURE



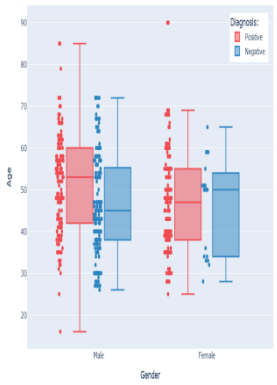
Copious section algorithm deals with n classifications as input to decision tree from decision tree output given as input to copious section algorithm where we get n classification binary output and also comments of patient medical diagnosis.

Fig 3: Analyzing Age-Stratified Distribution: Insights Exploring Variability through Box Plots



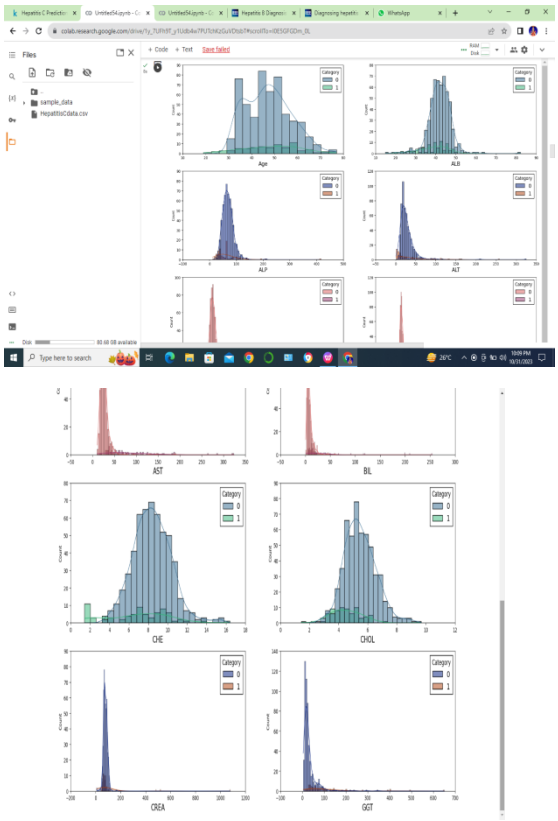
The analysis focused on the number of total counts across various diagnostic categories in the age-based diagnosis distribution. Perceptive Charting Identifies Trends in Age-Stratified Medical Diagnoses. A thorough analysis provides a deeper understanding of the distribution of diagnoses by age

FIG 4: Sex and Age Demographic Stratification Disaggregated Data Analysis



The diagnosis of diabetes indicates whether positive or negative, can vary between genders both male and female, variousevaluations required to determine the prevalence of diabetes among males and females.

FIG 5: Diabetic Hepatic Profiling: Analyzing Hepatic Complications



A bar chart for the provided data would require structuring it effectively

X-Axis: Categories - Age, ALB, ALP, ALT, AST, BIL, CHE

Y-Axis: Measurement values

Legend: Male and Female

TABLE 4: DIABETIC HEPA PROFILER ANALYSIS

Field	Description	
Age	Age of the subjects	
Sex	Gender of the subjects	
ALB	Albumin Blood Test	
ALP	Alkaline Phosphatase	
ALT	Alanine Transaminase	
AST	Aspartate Transaminase	
BIL	Bilirubin	
CHE	Acetylcholinesterase	

ALB: Albumin Blood Test results, a liver function indicator.

ALP: Alkaline Phosphatase, an enzyme found in the liver and bones.

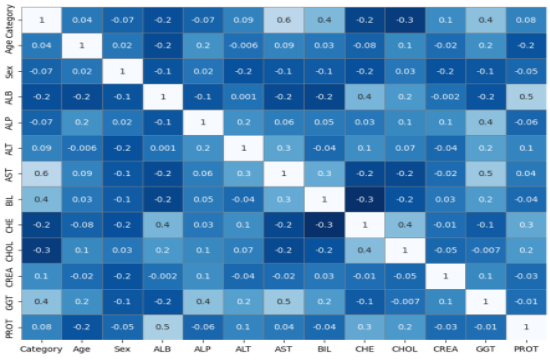
ALT: Alanine Transaminase, a liver enzyme.

AST: Aspartate Transaminase, another liver enzyme.

BIL: Bilirubin levels, a liver-related pigment.

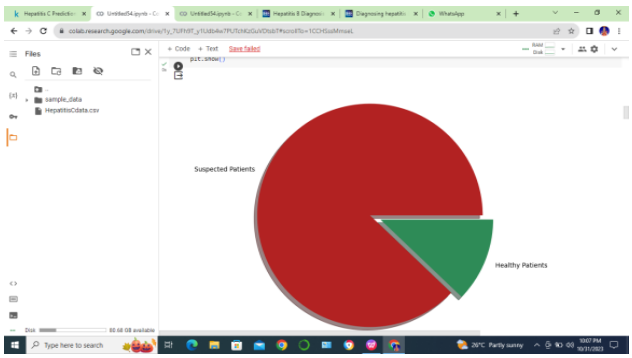
CHE: Acetylcholinesterase, an enzyme often associated with nerve function.

FIG 6: Diabetic Hepa Profiler Analysis



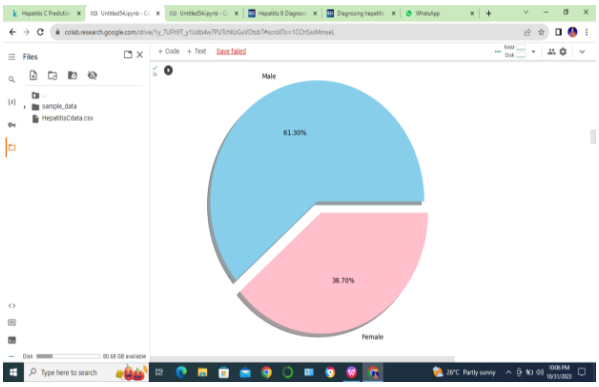
A correlation matrix for the mentioned content would show how variables are related to one another. It helps identify potential associations or dependencies between these factors.

FIG 7: Hepatitis C Predictive Models and Emerging Trends



Total Suspected Patients: 50 Total Healthy Patients: 75 labled in plots Label one slice as "Suspected Patients" and another as "Healthy Patients" to illustrate the distribution.

FIG 8 : Diagnosis of Diabetic heap profiler



In a subplot, the data can be visually divided into male and female categories, providing a clear comparisont this enables an effective gender-specific analysis of the medical conditions.

4. Conclusion:

"The copious section algorithm is helpful not only in detecting diabetic foot ulcer, but also in efficiently evaluating medical data and providing the best possible care for diabetic patients who have foot ulcer .Copious section algorithm helps support for diabetic patients and also non diabetic patients .

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