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Analysis and Diagnosis of Hemolytic Specimens by AU5800 Biochemical Analyzer Combined with AI Technology

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Abstract: There is a close correlation between biochemical analysis instruments and artificial intelligence, in biomedical engineering, biochemical analysis instruments produce a large number of complex data, including spectral data, mass spectrometry data, electrochemical data, etc. Artificial intelligence algorithms can be used to process and interpret this data, extract useful information from it, identify features and trends, and help researchers better understand biochemical processes. Moreover, artificial intelligence can be used to realize the data pattern recognition and classification of biochemical analysis instruments. Through machine learning techniques, algorithms can be trained to automatically identify differences between different samples or analysis results, helping to identify different biomolecules or compounds. It can also be used for fault diagnosis and maintenance of analytical instruments. By monitoring instrument performance data, algorithms can detect potential problems and provide repair recommendations, reduce instrument downtime, and between multiple biochemical analysis instruments, as well as with other laboratory equipment and databases, AI can be used for data consolidation and comprehensive analysis to help researchers obtain more comprehensive information. In this paper, the influence of Beckman 5800 automatic biochemical analyzer on the results of hemolysis test was discussed through the example of automatic biological differentiation instrument combined with artificial intelligence.

Keywords: Automatic Biochemical Analyzer; Intelligent Algorithm; Hemolytic Specimen; Biochemical Test.

1. Introduction

The Automatic Biochemical Analyzer AU5800 is a highly advanced clinical laboratory instrument that is highly automated and can automate a variety of biochemical analysis and assay processes, including the analysis of blood, urine and body fluid samples. This greatly improves laboratory efficiency and reduces the need for manual intervention, and this biochemical analyzer is versatile and can perform many different types of biochemical tests, including the detection of various biochemical parameters such as blood glucose, liver function, kidney function, myocardial enzymes, electrolytes, lipids, etc. This makes it widely used in clinical diagnosis[1]. And AU5800 adopts advanced optical and electrochemical detection technology, AU5800 can be configured and customized according to the needs of the laboratory to adapt to different application requirements, can provide high precision and accurate analysis results, which is very critical for clinical diagnosis and disease monitoring, automatic analysis instrument has high throughput analysis ability, can handle a large number of samples at the same time. Ideal for busy clinical laboratory environments. It can process a large number of samples in a relatively short time, providing fast results[2].

The automatic biochemical analyzer AU5800 is widely used in the clinical medical field, especially in the clinical laboratory. It is used in various blood tests, especially in chronic disease monitoring, epidemic monitoring, kidney function assessment, liver function assessment, blood lipid detection, diabetes management and so on[3]. Its high-throughput and high-precision properties make it ideal for handling large numbers of samples and delivering fast and accurate results. With the continuous progress of medical technology, the application field of automatic biochemical analyzer AU5800 will continue to expand, and it is expected to play a greater role in clinical diagnosis and medical research.

2. Organization of the Text

The fully automated biochemical analyzer AU5800 typically uses a range of algorithmic models for data analysis and results calculation to ensure accuracy and reliability. These algorithm models include, but are not limited to, the following:

2.1. Photometry and Colorimetry

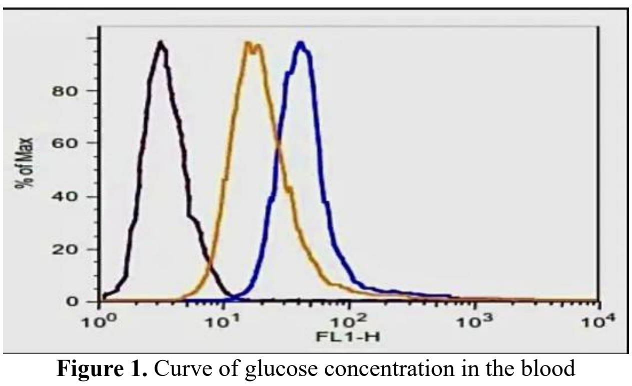


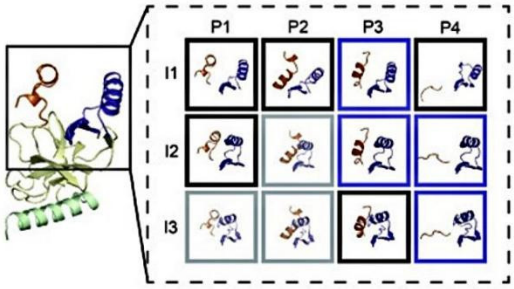
Figure 1. Curve of glucose concentration in the blood

These algorithms are used to measure absorbance or color change to determine the concentration of a particular analyte in a sample. For example, the concentration of glucose in the blood is usually measured using photometry.

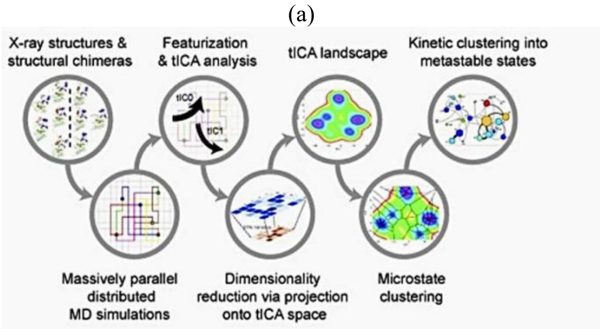
Comparison of histogram from flow analysis showing the inhibition of glucose uptake by phloretin in Jurkat cells (Black: negative control cells; orange: in the presence of phloretin; blue: without phloretin).

2.2. Enzyme Kinetic Model

Enzyme kinetic models are often used to analyze enzyme activity in biochemical reactions. Fully automated bioanalyzers are commonly used to measure biochemical parameters in body fluid samples, including liver function, kidney function, myocardial enzymes, etc. [4]. The determination of these parameters usually depends on enzyme-catalyzed reactions, in which enzyme activity is key.



(a)



(b)

Figure 2. Enzyme kinetic model and Markov state model

On the basis of enzyme kinetics simulation, it provides the basis for understanding enzyme activity and reaction mechanism, and the automatic bioanalyzer applies these models to the actual clinical biochemical analysis, and uses the method of machine learning to build the Markov state model. The SET-I Domain-mediated allosteric regulation mechanism was extracted and verified by mutation experiments (K382P, I293G and E292G), ITC and stop-flow mechanics experiments. By analyzing and comparing SET8 cancer mutation data in cBioPortal database, the mechanism of how allosteric region affects enzyme activity was further confirmed [5].

2.3. D. Immunoassay:

Used to measure immunoassay parameters, such as the concentration of antibodies or antigens. These assays typically involve immunoassay methods such as enzyme-linked immunosorbent assay (ELISA) and use associated data analysis algorithms.

The fully automated biochemical analyzer AU5800 typically integrates these different types of algorithmic models to address a wide range of different types of biochemical parameters and analytical needs. The selection and optimization of these algorithm models are key factors in ensuring instrument performance and results accuracy.

3. Methodology

The automatic biochemical analyzer AU5800 can often be used to detect a variety of biochemical parameters in the blood, including liver function, kidney function, myocardial enzymes, electrolytes, lipids, and more. For blood samples, especially those with hemolysis, the AU5800 is usually able to perform a range of tests, but there are some key factors to consider.

3.1. Hemolytic Sample Identification

The AU5800 usually tests the sample for hemolysis, as hemolysis may affect the accuracy of the analysis results. Instruments will usually use optical methods or other techniques to detect hemolysis and warn or exclude the hemolysis sample.

Because hemoglobin has peroxide-like activity, it can catalyze hydrogen peroxide (H202) to release new ecological oxygen. This experiment takes advantage of this property of hemoglobin, and according to the color rendering principle of TMB, The remaining liquid A (including H202) and liquid B (including TMB) of the enzyme-linked immunosorbent assay (ELISA) kit with TMB as the chromogen is used as the chromogenic agent, and the depth of its color is proportional to the concentration of hemoglobin within a certain range, and the change of its absorbance is measured at a specific wavelength, and then the concentration of hemoglobin is calculated.

Table 1. Hemoglobin concentration sample in hemolytic serum specimen

sample	Batch Hemoglobin concentration (g/L)		Batch hemoglobin concentration (g/L)	
	-x±s	CV (%)	- x±s	CV (%)
Sample1	2. 61±0. 06	2.29	3. 00±0. 12	4.00
Sample2	6. 03±0. 12	1.99	7. 01±0. 15	2.14
Sample3	8. 71±0. 14	1.61	9. 07±0. 34	3.75

3.2. Detection Method

(1) Testing instrument: Hitachi 7060 automatic analyzer.

(2) Detection reagent: The remaining liquid A and B of the enzyme-linked immunosorbent assay kit of Hepatitis B two-half detection project produced by 3V Company, using liquid B as reagent 1(240) and liquid A as reagent 2(60 U).

(3) Analysis method: continuous monitoring method (rate A), analysis point of 6~12 points, analysis wavelength of 660 nm.

(4) Calibration type: linear two-point calibration.

(5) Calibration solution: Calibrate Sysmex K-21 blood cell counter with Sysmex original imported quality control product, test fresh whole blood samples with calibrated blood cell counter, and dissolve the measured hemoglobin value into 10g/L hemoglobin calibration solution with deionized water.

(6) Repeatability test: 3 serum specimens with different levels of hemolysis were selected for repeated detection for 20 times, and 3 serum specimens with different levels of hemolysis were selected for subpackaging and frozen storage, and tested once a day for a total of 20 days.

(7) Detection of linear range: The hemoglobin calibration solution of 50, 4540, 35, 30_25_20, 15,10,5, 4,3, 2 and l g/L were prepared by the method of preparing hemoglobin calibration solution for double detection to determine the

linear range.

(8) Recovery test: 3 serum samples with different hemolysis degrees were taken respectively, and 5 g/L hemoglobin standard solution was added to detect the recovery rate.

(9) Interference test :D bilirubin interference test. Three serum samples with different hemolysis degrees were added with deionized water and bilirubin standard solution at a ratio of 1:1, and their hemoglobin concentrations were detected respectively, and their relative errors were calculated. 2 lipid blood interference test [6-9]. Gross lipid blood samples were taken to detect the concentration of triglyceride, and then 3 serum samples with different hemolysis degrees were added with deionized water and gross lipid blood samples at a ratio of 1:1 to detect their hemoglobin concentrations and calculate their relative errors.

3.3. Data Result

Hemolysis releases intracellular components in the blood, such as hemoglobin, which may affect the determination of certain parameters, such as hemoglobin concentration or potassium ion concentration. Therefore, for hemolytic samples, the instrument may require special calibration and data processing [10].

Among them, a series of hemoglobin standard solution was prepared by the preparation method of hemoglobin standard solution for the detection result of linear range. The linear equation of this method is Y=0.133 10 1.009X, r=0.999 when the hemoglobin concentration reaches 30 g/L, the detection result shows an obvious upward trend. 2.3 Detection results of the recovery test: 5 g/L hemoglobin standard solution was added to the hemolytic serum samples with hemoglobin of 2.66 and 6.28.9.06 g/L at a ratio of 1:1, and the average recovery rate was 101.59%, as shown in Table 2.

Table 2. Linear range of detection results

sample	Actual hemoglobin concentration (g/L)	Recovery of hemoglobin concentration (g/L)	Recovery rate (%)
Sample1	3.83	3.70	96.61%
Sample2	5.64	5.78	102.48%
Sample3	7.63	7.43	105.69%

As a functional protein in red blood cells, hemoglobin plays an important role in oxygen transport, H202 decomposition, electron transfer and so on related to oxygen and energy metabolism [11]. When red blood cells are destroyed in the body or in vitro, hemoglobin will be released into the serum, therefore, the detection of the content of hemoglobin in the serum can indirectly reflect the degree of destruction of red blood cells, when red blood cells are destroyed in vitro, that is, the specimen is usually said to have hemolysis, and the concentration of hemoglobin in the serum can indirectly reflect the degree of hemolysis of the specimen.

4. Conclusion

Automatic biochemical analyzer is a commonly used instrument for detecting biochemical indicators in clinical practice, and plays an important role in assisting diagnosis, therapeutic effect and prognosis evaluation of clinical diseases. Most studies show that the Beckman 5800 automatic biochemical analyzer is easy to operate and has high accuracy, with detection accuracy of up to 97%. However, in the process of clinical testing, hemolysis will have a certain impact on the test results. After hemolysis, granulocytes and red blood cells were destroyed to a certain extent, and the concentration of mitochondrial enzymes was increased, which led to the improvement of the expression levels of ALT, AST, LDH and other indicators detected by automatic biochemical analyzer. At the same time, the hemolysis of the specimen will lead to the destruction of a large number of red blood cells, and the volume of broken red blood cell fragments is smaller than that of normal red blood cells. The instrument calculates the average volume of red blood cells, thus reducing the hematocrit. In addition, some small red blood cell fragments will be mistaken for platelets by the instrument, thus interfering with the platelet count, resulting in a large difference in the content of K+ in and out of cells detected by the automatic biochemical analyzer. Therefore, the results of the automatic biochemical analyzer will increase when detecting samples after hemolysis "In addition, there will be certain errors in the absorption and dispersion of colored substances in the hemolysis specimens, which will affect the color reaction in the biochemical detection, resulting in abnormal detection results.

Therefore, the future vision of a fully automated bioanalyzer Beckman AU5800 combined with artificial intelligence (AI) is very exciting and will bring many innovations and advances to medical diagnostics and life science research, where the AU5800 can automatically interpret analytical results and generate diagnostic reports. AI can provide more precise diagnostic recommendations based on large amounts of clinical data and case history, helping doctors quickly formulate treatment plans. It can also be used to monitor instrument performance and analysis results in real time, identify abnormal conditions, and automatically take measures. This will help improve the efficiency of the laboratory and the accuracy of the results, help identify potential disease risk factors, and predict the development of the disease in advance, facilitating early intervention and diagnosis. The future vision of combining the AU5800 with artificial intelligence includes more accurate diagnostics, personalized medicine, disease prediction, scientific innovation, and improved medical efficiency. This will help drive advances in the medical field and provide better medical services and health management

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