Research article

Decision tree distinguish affective disorder diagnosis from psychotic disorder diagnosis with clinical and lab factors

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A B S T R A C T

Background: Affective symptoms usually occur at the same time of psychotic symptoms. An effective predictive method would help the differential diagnosis at an early stage of the mental disorder. The purpose of the study was to establish a predictive model by using laboratory indexes and clinical factors to improve the diagnostic accuracy.
Methods: Subjects were patients diagnosed with psychiatric disorders with affective and/or psychotic symptoms. Two patient samples were collected in the study (n = 309) With three classification methods (logistic regression, decision tree, and discriminant analysis), we established the models and verified the models.
Results: Seven predictors were found to be significant to distinguish the affective disorder diagnosis from the psychotic disorder diagnosis in all three methods, the 7 factors were Activities of daily living, direct bilirubin, apolipoproteinA1, lactic dehydrogenase, creatinine, monocyte count and interleukin-8. The decision tree outperformed the other 2 methods in area under the receiver operating characteristic curve, and also had the highest percentage of correctly classification.
Conclusion: We established a predictive model that included activities of daily living, biochemical, and immune indicators. In addition, the model established by the decision tree method had the highest predictive power, which provided a reliable basis for future clinical work. Our work would help make diagnosis more accurate at an early stage of the disorder.

1. Introduction

Nearly 1 billion people worldwide suffered from mental disorders [1], of which affective disorders and psychotic disorders are two major categories. The psychotic symptoms include paresthesia, hallucination, delusional experience, thinking disorder, abnormal emotional experience and abnormal behavior, etc. Disorders associated with psychotic symptoms include schizophrenia, acute and transient psychotic disorders, dissociative conversion disorder, etc. The affective symptoms include low mood, decreased interest, slow thinking, attention and memory loss, self-denial, poor appetite, reduced activity, and even pessimism, despair, they may even approach suicide by searching the internet for information and news about self-harm and suicidal behavior [2], and people with mood disorders are more likely to attempt lifetime suicide [3], etc. Disorders in relation to affective symptoms include social anxiety disorder,

major depressive disorder, bipolar disorder, etc. The two types of symptoms often occur together. For example, negative symptoms of schizophrenia are withdrawn, lazy, and unwilling to interact with others, very similar to symptoms of affective disorders. Affective symptoms may occur in the early stage of schizophrenia or at other times [4].

Inflammation is a necessary process in the body, but can damage host cells if overdone. Inflammatory factors are closely associated with affective disorders symptoms [5], studies have shown that the levels of IL-1β, IL-2, IL-6 and TNF-A increased and the level of IL-8 decreased in patients with major depression disorder [6]. In a study of depression in the elderly, higher levels of IL-6 and IL-8 were found in the cerebrospinal fluid [7]. IL-8 may also be related to anxiety symptoms [8]. Serum IL-6, IL-8 and TNF-a levels have been found to be elevated in both depressive and manic patients with bipolar disorder [9, 10]. Serum cholesterol (TC), triglyceride (TG) and free thyroxine (FT4) levels were significantly

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reduced in patients with depression and suicidal tendencies [11]. Thyroid dysfunction also presented in mood disorders [12]. In addition, studies on abnormal metabolism of blood biochemical indicators were reflected in patients with bipolar disorder, and the levels of hemoglobin (Hb), UA, ALT, LDH, AST and GGT in patients with bipolar disorder were higher than those in patients with depression [13].

Inflammatory responses are associated with psychotic disorders. Studies have shown that the levels of IL-2, IL-6 and IL-8 in peripheral blood of patients with schizophrenia were significantly higher than those of normal controls [14], IL-6 is a marker of acute exacerbation [15], IL-4 level was significantly lower in schizophrenia than normal controls [16]. In addition, studies of inflammatory factors in the cerebrospinal fluid of patients with schizophrenia have shown that IL-8 level was significantly elevated [17]. Schizophrenia patients had higher blood glucose (GLU), triglyceride (TG), cholesterol (TC), and low-density lipoprotein (LDL) levels than healthy controls [18]. Patients with psychotic disorders had higher level of prolactin (PRL), lower level of three-point thyroxine (T3) than healthy controls, but had no differences in thyroid stimulating hormone (TSH) and free thyroxine (FT4) [19]. Monocyte (MON), a differential element in white blood cell count, was elevated in severe psychotic disorders [20].

Different medications have been used for psychotic disorders and affective disorders. Antipsychotic drugs are mainly represented by dopamine receptor blockers, while 5-HT reuptake inhibitors are the first-line choice for anti-affective drugs. Therefore, misdiagnosis of these two categories of disorders would lead to a wrong treatment and delay the best treatment opportunity. If accurate diagnosis can be made at the early stage of the disorder, the cure rate of the treatment would be improved, that would reduce the economic and social burden. Therefore, an effective and easy prediction model would help the differential diagnosis at the early stage.

These studies suggested that mental disorders, including psychotic disorders and affective disorders, are associated with changes in the immune system and the metabolism of the body. In clinical work, blood test is a necessary step before the diagnosis. Therefore, it is feasible to seek for factors in the blood that can classify the disorders. The learning of decision tree was essentially to induct a set of classification rules from the training set, to obtain a decision tree with less contradiction with the data set, and at the same time, it had good generalization ability. The loss function of decision tree learning was usually a regularized maximum likelihood function, and usually a heuristic method was used to approximate this optimization problem. Decision trees were easy to understand and implement. Therefore, the purpose of the study was to evaluate the advantages of decision tree as a method for establishing a clinical predictive model.

2. Methods

2.1. Sample

According to the diagnostic criteria in the International Statistical Classification of Diseases and Related Health Problems 10th Revision (ICD-10), the recruited participants were diagnosed with major depressive disorder (MDD), bipolar disorder (BP), or unspecified mood (affective) disorders, which were included in the affective disorders group. Others were diagnosed with schizophrenia (SCZ), acute and transient mental disorders, and 12 patients with separation symptoms were classified as dissociative (conversion) disorders, which were included in the psychotic disorders group. The clinical manifestations of acute transient mental disorders collected in this paper were mainly hallucinations, delusions, disorganized speech and disorientation. The clinical manifestations of dissociative (conversion) disorders collected in this paper were mainly disorganized speech, behavior disorder, impulse and other behaviors. Their behavior in the clinical manifestation was closer to the state of psychosis, so they were divided into the psychosis group. The study was approved by the Medical Research Ethics Review Committee of

the Fourth People's Hospital of Hefei, and the participants signed the forms before the hospital admission.

Two patient samples were collected in the study. The first sample (n = 224) was collected from June 15, 2021 to September 10, 2021, of which 108 patients were included in the training dataset for the establishment of the clinical prediction model, and 116 patients were included in the retrospective test dataset (test dataset 1). The second sample was collected from October 26, 2021 to November 21, 2021, with a total of 85 patients as a prospective test dataset (test dataset 2).

The inclusive criterias were: (1) diagnosed with major depressive disorder (MDD), bipolar disorder (BP), mood situation disorder, schizophrenia, acute and transient mental disorders, or separation and conversion disorders; (2) age range was 11–76 years; (3) first-time hospital admission; (4) less than 2 months medication treatment. The exclusive criteria Included participants who were pregnant or breastfeeding, had a clinically significant substance use disorder, seizure, organic brain syndrome or a history of head injury.

2.2. Study design

The study protocol was reviewed and approved by the Ethics Committee of Anhui Mental Health Center. The data were extracted from the medical records and blood test report, the 71 variables included 5 general demographic variables, 5 diagnostic variables, 7 questionnaires, 28 routine biochemical items, 17 lab immune items, and 9 blood count items. Prior to data extraction and analysis, personally identifiable information was replaced with a code to protect personal privacy of patients. We used SPSS22.0 software, with three types of classification methods (logistic regression, decision tree, discriminant analysis) in the training dataset to set up the models, then tested the three models respectively in the validation dataset 1 (retrospective) and the validation dataset 2 (prospective). Finally, among the three, we chose the best clinical prediction model. Experimental flow chart was shown in Figure 1.

3. Data collection

3.1. Blood data

Early morning fasting blood was collected, 2 ml of Ethylenediamine Tetraacetic acid dipotassium (EDTA-2K) anticoagulant blood was mixed upside down, and 5 ml of whole blood was collected with a dry tube. Serum was extracted with 4 * 4000 low-speed centrifuge, and 1 mL of serum was stored in a low-temperature refrigerator at −80 °C for use. We have used the Beckman LH750 automatic blood analyzer to test patients' blood cell count, the Roche C702 automatic biochemical analyzer to test the content of biochemical indicators of patients, with automatic chemiluminescence analyzer test indicators to test Roche C602 thyroid function, the Roche E601 automatic chemiluminescence analyzer to test six levels of sex hormones, and Siemens DPC1000 automatic chemiluminescence analyzer to test patients' inflammatory cytokines (See supplementary materials for specific chemical testing methods). All these instruments used the original reagent, and the state and quality control of the instruments met the requirements of the national laboratory quality assessment.

3.2. Questionnaires

(1) Hamilton Depression Scale (HAMD) [51], the evaluation was mainly based on the psychological symptoms of patients responding to 7 factors including anxiety somatization, weight, cognitive disorder, day-night change, block, sleep disorder and sense of despair. (2) Hamilton Anxiety Scale (HAMA) [52], the evaluation mainly reflects the psychological symptoms of patients from the two factors of physical anxiety and mental anxiety. (3) Positive symptom scale. The higher the score, the more serious the positive symptoms. (4) Negative symptom
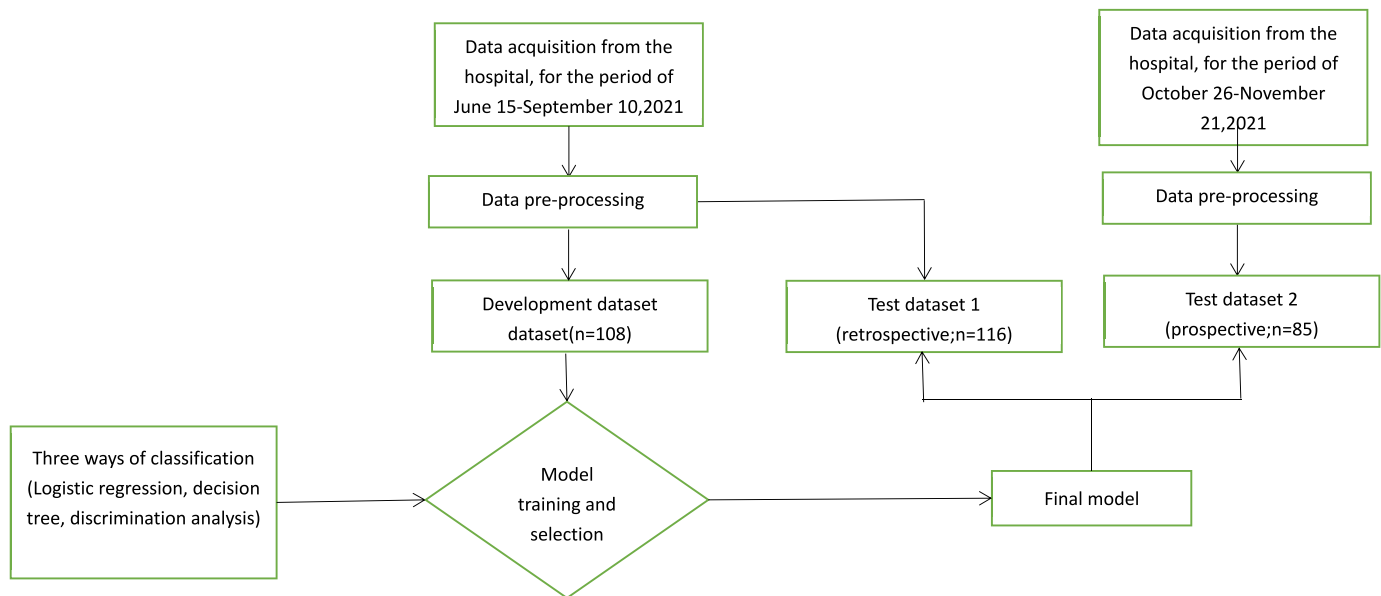
Figure 1. The workflow chart of the entire study.

scale. The higher the score, the more serious the negative symptoms. (5) Daily Living Ability Scale (ADL) [53]. (6) Concise Psychiatric Rating Scale (BPRS) [54], the evaluation mainly reflects the mental status of patients from anxiety and depression, lack of vitality, thinking disorder, activation, hostile suspicion and other factors. (7) Social function deficit Screening scale, which evaluates patients' social life ability from three aspects.

4. Statistical analysis

To establish a clinical predictive model for diagnosing affective disorders or psychotic disorders, the study collected three datasets, one as the training dataset, in which three methods (logistic regression, decision tree and discriminant analysis) were used to set up the predictive models, then the three models were tested in validation dataset 1 and validation dataset 2 respectively. The prediction ability was mainly based on the area under receiver operating characteristic curve (AUC) score. The greater AUC score, the higher the prediction ability of the model. The secondary criterion was the percentage of correctly classified instances. To select the candidate predictors, a total of 71 variables were tested by the least absolute shrinkage and selection operator (LASSO) variable selection method. Then, the variables selected by LASSO analysis were used as predictors, and either affective disorders or psychotic disorders was the dependent variable. Logistic regression, decision tree and discriminant analysis were used to established the clinical predictive model for diagnosis.

To validate the predictive models, the three models were tested with validation dataset 1 (backtracking) and validation dataset 2 (prospective) respectively, and the areas under the ROC curve and the percentages of correct classification for each model were calculated and compared.

5. Results

5.1. Sample character

A total of 309 patients were included in the study. Age ranges from 11 to 76 (31.65 ± 15.35 years), and two-thirds were females. See Table 1 for the demographic and sociological data of the subjects. There were no significant difference in age, sex ratio, educational status, occupation and marital status between the affective disorders group and the psychotic disorders group in the three datasets.

5.2. Predictor selection

The 71 variables were included in this study. The LASSO coefficient graph was obtained by LASSO variable selection method, and 7 predictive variables were selected, namely DBI, APOA1, LDH, ADL, CREA, MON, and IL-8. The penalty is 0.460, the normalize "R square" is 0.539, the normalization coefficient sum is 0.063, and the apparent prediction error is 0.461.

5.3. Development of three predictive models

5.3.1. Logistic regression

We conducted a binary logistic regression, in which DBI, APOA1, LDH, ADL, CREA, MON and IL-8 were entered as independent variables, and the affective disorders or psychotic disorders was entered as dependent variable. This binary regression model included 108 cases (73 affective disorders vs. 35 psychotic disorders), and it showed an AUC of 0.787, and 78.7% correctly classified instances. Calibration was obtained by the Hosmer-Lemeshow test (p = 0.098). The regression equation showed that DBI and ADL were negatively correlated with diagnosis, while APOA1,LDH,CREA, MON and IL-8 were positively related. Table S1 for the established regression equation model.

5.3.2. Decision tree

Based on the decision tree method, the factors influencing the diagnosis (affective disorders or psychotic disorders) were analyzed, including DBI, APOA1, LDH, ADL, CREA, MON and IL-8. The final classification regression tree (CRT) model formed was shown in Figure 2, and the percentage of correct classification was 86.1%. The decision tree was divided into six layers according to the seven factors affecting diagnosis. The nodes of the decision tree branch based on LDH, indicating that LDH had the most significant influence on diagnosis. In addition to LDH, according to the influence of independent variables from large to small order was IL-8, CREA, APOA1, DBI, ADL, MON.

5.3.3. Discrimination analysis

The dataset 1 were used as training samples, and Fisher discriminant analysis was used to establish the discriminant function. DBI, APOA1, LDH, ADL, CREA, MON and IL-8 were entered as independent variables and the diagnosis category (affective disorders or psychotic disorders) was entered as dependent variable. The coefficients of Fisher's

Table 1. Comparisons of sociodemographic features among the three datasets.

| Variable	Development dataset				Test dataset 1 (retrospective)				Test dataset 2 (prospective)			
	Total (n = 108)	Affective disorders (n = 73)	Psychotic disorders (n = 35)	P value	Total (n = 116)	Affective disorders (n = 56)	Psychotic disorders (n = 60)	P value	Total (n = 85)	Affective disorders (n = 61)	Psychotic disorders (n = 24)	p value
Age, y	31.96 ± 16.49	33.1 ± 17.86	29.6 ± 13.05	0.25	31.29 ± 14.04	30.61 ± 15.23	31.93 ± 12.98	0.77	30.86 ± 15.69	28.82 ± 14.78	36.04 ± 17.03	0.06
Gender,%				0.67				0.65				0.24
Female	67 (62.04)	44 (60.27)	23 (65.71)		93 (80.17)	46 (82.14)	47 (78.33)		49 (57.65)	38 (62.30)	11 (45.83)	
male	41 (37.96)	29 (39.73)	12 (34.29)		23 (18.83)	10 (10.76)	13 (21.67)		36 (42.35)	23 (37.70)	13 (54.17)	
Marital status,%				0.70				0.10				0.50
Single	60 (55.56)	43 (58.90)	17 (48.57)		55 (51.89)	29 (51.79)	26 (43.33)		48 (56.47)	34 (55.74)	14 (58.33)	
Married	42 (38.89)	26 (35.61)	16 (45.71)		55 (51.89)	27 (48.21)	28 (46.67)		34 (40)	24 (39.34)	10 (41.67)	
Divorced	6 (5.56)	4 (5.48)	2 (5.71)		6 (5.17)	0 (0)	6 (10.00)		3 (3.53)	3 (4.92)	0 (0)	
Education level, %				0.11				0.75				0.91
Illiteracy	7 (6.48)	3 (4.11)	4 (11.43)		6 (5.17)	2 (3.57)	4 (6.67)		2 (2.35)	2 (3.28)	0 (0)	
Primary school	11 (10.19)	4 (5.48)	7 (20)		11 (9.48)	6 (10.71)	5 (8.33)		9 (10.59)	4 (6.56)	5 (20.83)	
Junior high school	45 (41.67)	33 (45.20)	12 (34.29)		38 (32.76)	16 (28.57)	22 (36.67)		25 (29.41)	21 (34.43)	4 (16.67)	
Senior high school/ technical secondary school	22 (20.37)	16 (21.92)	6 (17.14)		27 (23.28)	15 (26.79)	12 (20)		25 (29.41)	16 (26.23)	9 (37.50)	
Junior college/university	22 (20.37)	16 (21.92)	6 (17.14)		33 (28.45)	17 (30.36)	16 (26.67)		22 (25.88)	18 (29.51)	4 (16.67)	
High level intellectual	1 (0.93)	1 (1.37)	0 (0)		1 (0.86)	0 (0)	1 (1.67)		2 (2.35)	0 (0)	2 (8.33)	
Occupation,%				0.30				0.06				0.60
Unemployed	38 (35.19)	27 (36.99)	11 (31.43)		44 (37.93)	16 (28.57)	28 (46.67)		25 (29.41)	17 (27.87)	8 (33.33)	
Farmer	7 (6.48)	3 (4.11)	4 (11.43)		9 (7.76)	6 (10.71)	3 (5.00)		3 (3.53)	3 (4.92)	0 (0)	
Worker	1 (0.93)	1 (1.37)	0 (0)		1 (0.86)	0 (0)	1 (1.67)		0 (0)	0 (0)	0 (0)	
Student	42 (38.89)	30 (41.10)	12 (34.29)		34 (29.31)	22 (39.29)	12 (20.00)		35 (41.18)	27 (44.26)	8 (33.33)	
Professionals/civil servant	1 (0.93)	0 (0)	1 (2.86)		4 (3.45)	3 (5.36)	1 (1.67)		7 (8.24)	4 (6.56)	3 (12.5)	
Company employee/ individual	16 (14.81)	10 (13.70)	6 (17.14)		19 (16.38)	8 (14.29)	11 (18.33)		12 (14.12)	8 (13.11)	4 (16.67)	
Retired	1 (0.93)	0 (0)	1 (2.86)		2 (1.72)	1 (1.79)	1 (1.67)		2 (2.35)	1 (1.64)	1 (4.17)	
Other	2 (1.85)	2 (2.74)	0 (0)		3 (2.59)	0 (0)	3 (5.00)		1 (1.18)	1 (1.64)	0 (0)	
duration of illness(mean), months	108 (12.09)	73 (12.75)	35 (10.71)	0.50	116 (11.82)	56 (11.30)	60 (12.30)	0.73	85 (10.13)	61 (11.29)	24 (7.20)	0.14
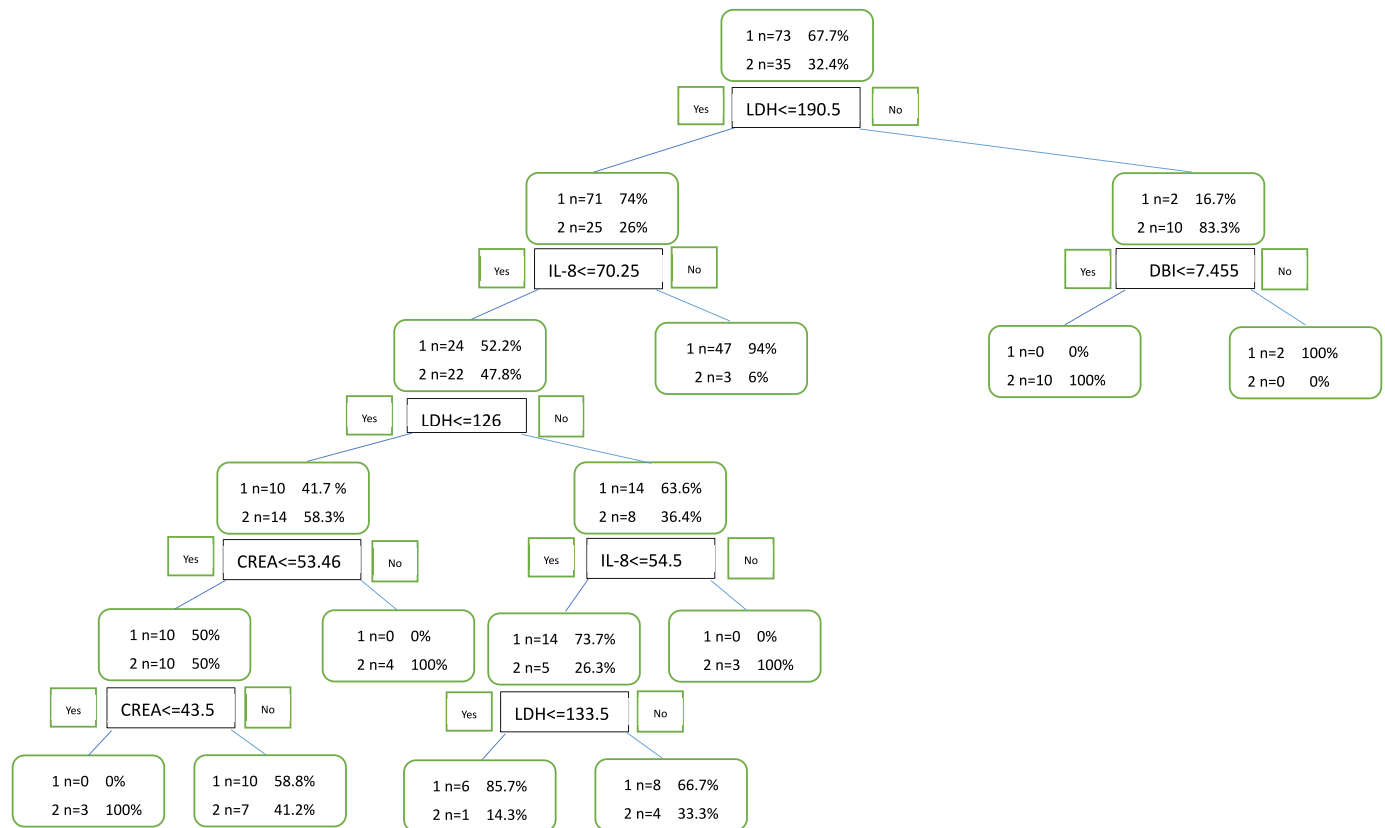
Figure 2. Decision Tree model.

discriminant function obtained were shown in Table S2, and the percentage of correct classification was 73.1%. The coefficients of Fisher's discriminant function obtained were as follows:

$F_1 = -48.211 + 0.680 * ADL + 0.374 * DBI + 32.650 * APO + 0.411 * CREA + 0.009 * LDH + 17.837 * MON + 0.003 * IL-8;$
$F_2 = -55.385 + 0.600 * ADL + 0.084 * DBI + 34.962 * APOA1 + 0.446 * CREA + 0.029 * LDH + 21.521 * MON + 0.003 * IL-8.$

5.3.4. Validation and comparison of three clinical prediction models

We formed 3 models (logistic regression, decision tree and discriminant analysis) by using 7 predictors. On the basis of validating the three models in two test datasets, we chose the model set by the decision tree as the ultimate model because it outperformed the other 2 models in AUC (Test dataset 1: logistic regression = 0.812, decision tree = 0.873, discriminant analysis = 0.796; Test dataset 2: logistic regression = 0.764, decision tree = 0.926, discriminant analysis = 0.772. See Figure 3(A, B, C, D, E, F, G, H, I) and Table 2). The decision tree model also had the highest percentage of correctly classified instances of affective disorders in the test dataset 1 and test dataset 2 (see Table S3).

6. Discussion

The study found that the 7 indicators, ADL, DBI, APOA1, LDH, CREA, MON and IL-8, were significant in distinguishing the two types of disorders, among three classification methods (logistic regression, decision tree and discriminant analysis), it was found that the model established by decision tree had the best prediction ability, with the largest AUC and the highest percentage of correct classification.

Logistic regression was a traditional statistical method while decision tree and discriminant analysis were new machine learning methods. We

have used these three methods to build the models. We then selected the model with the highest predictive power by comparing which one was more suitable for medical statistical processing.

With the progress of science and technology, artificial intelligence methods were used in the field of medicine more and more [21, 22, 23, 24]。 Studies have proven the advantage of machine learning, and the sensitivity-specificity difference ranged from 0.035 to 0.927 [25]. Decision tree was a machine learning processing, and it had a strong statistical analysis ability and had a less requirement on the data quality, such as incomplete date (missing key indicators) and noisy data (numerical errors/anomalies) [26]. The data used in the study came from the hospital database, there might be a few flaws such as lack of the blood indicators in a few patients. However, the decision tree could predict the occurrence, development and prognosis of disorders in the circumstance of lack of data. Consistently, a previous study used the logistic regression, decision tree algorithm and XG Boost three methods to establish a model about whether need blood transfusion to patients, the results suggested that the decision tree model had the best ability to identify transfusion/non-transfusion, and the more parameters were included in the model, the more prominent the advantages of the decision tree model was, the time advantage was also incomparable [26].

ADL evaluated the daily living ability of patients. A study has shown that the dysfunction of patients with psychotic disorders was substantial, complex and persistent [27]. Physical function and complex activities in affective disorders were also decreased [28]. Both were deficient in daily living, with patients with psychotic disorders performing worse than those with affective disorders [29]. The score on the scale could be used as one of the indicators to distinguish the two disorders.

Inflammatory immune response and metabolic response, as well as their interaction, play an important role in the pathophysiology of psychotic disorders and affective disorders. DBI is serum direct bilirubin, which is the final product of heme metabolism and acts as an endogenous
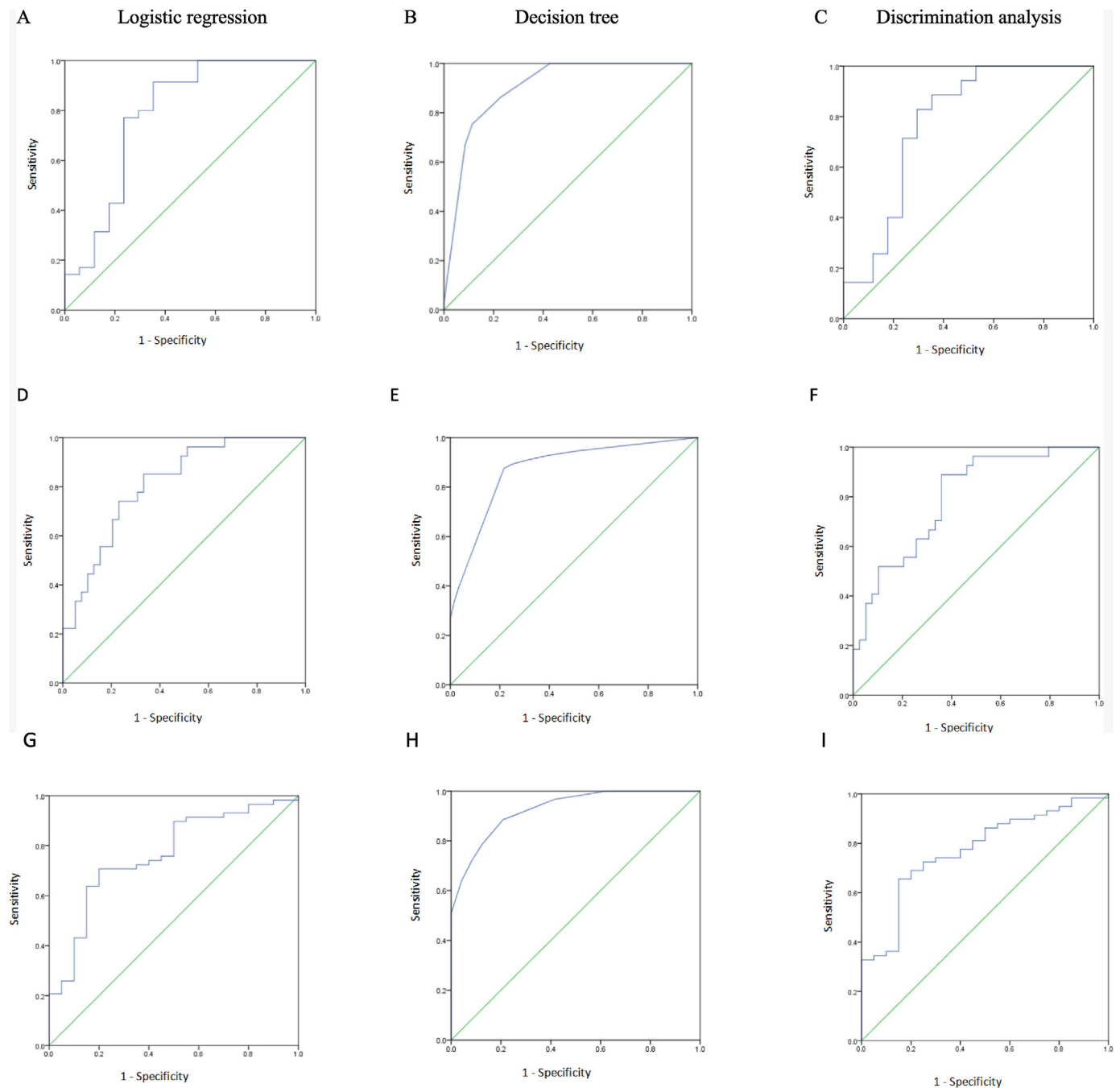
Figure 3. ROC curve of three models in three datasets. ROC curve of models formed by logistic regression in development dataset (A), test dataset 1 (D), test dataset 2 (G); ROC curve of models formed by decision tree in development dataset (B), test dataset 1 (E), test dataset 2 (H); ROC curve of models formed by discrimination analysis in development dataset (C), test dataset 1 (F), test dataset 2 (I); A Logistic regression B Decision tree C Discrimination analysis.

antioxidant. It played a role in the pathogenesis of patients with bipolar disorder, while the level of direct bilirubin was low in patients with depression [30]. High serum bilirubin levels were associated with increased total antioxidant capacity and provided protection against oxidative stress-induced disorder [31]. Studies in patients with psychotic disorders have shown that direct bilirubin concentrations were inversely associated with metabolic syndrome and systemic inflammation [32, 33].

Table 2. AUC of the three predictive models in the three datasets.

	Development dataset		Test dataset 1		Test dataset 2	
	Value	95% CI	Value	95% CI	Value	95% CI
Logistic regression	0.787	0.634–0.939	0.812	0.711–0.913	0.764	0.645–0.883
Decision Tree	0.9	0.832–0.969	0.873	0.808–0.938	0.926	0.870–0.982
Discrimination analysis	0.776	0.619–0.934	0.796	0.689–0.902	0.772	0.659–0.885

APOA1 is one of the main components of high-density lipoprotein cholesterol, which is mainly synthesized in the liver. It has anti-atherosclerosis, antioxidant, anti-inflammatory and immunomodulatory effects [34]. In recent years, it has been often mentioned in patients with psychotic disorders and affective disorders. Studies have found that APOA1 decreased in the cerebrospinal fluid and peripheral tissues of patients with psychotic disorders [35]. This might be related to mitochondrial dysfunction and increased oxidative stress in patients with psychotic disorders [36]. Patients with affective disorders also had lower levels of APOA1 [37,38].

LDH exists in various tissues and organs of human body. It is a crucial redox enzyme in the glycolysis pathway of organisms and can catalyze the reversible oxidation of lactic acid to pyruvate [39]. Studies have shown that changes in LDH concentration in brain tissue affected synaptosome function [40], which was a direct marker of mitochondrial dysfunction [41].

CREA is a metabolite of muscle in human body, which has anti-apoptotic, anti-excitatory toxicity and anti-oxidation properties [42]. Creatinine has a neuroprotective effect [43], it participated in the extension of dendrites and axons, and promoted the growth and storage of neurons in the brain [44]. Studies have shown elevated creatinine levels in people with psychotic disorders and affective disorders [45, 46], which might be a potential protective effect of creatinine involved in body metabolism.

MON participated in the immune response, phagocytosis and release of pro-inflammatory cytokines [47]. Monocyte alterations have been reported in the studies of psychotic disorders, with a significant increase in the monocyte numbers in patients [48]. This also indirectly confirmed that monocytes were involved in the anti-inflammatory effect of patients with psychotic disorders, and proved the inflammatory hypothesis in psychotic disorders.

IL-8 is one of the major inflammatory cytokines, and is a pro-inflammatory cytokine produced by macrophages, microglia and other cells. The levels of IL-8 in the cerebrospinal fluid and peripheral blood of patients with psychotic disorders were increased and correlated with the severity of the symptoms [49, 50]. IL-8 level was generally elevated in patients with affective disorders, with the exception of depression [5].

7. Limitation

The limitation of the study was, since we included patients on short-term medication, these patients had already taken antipsychotic or antidepressant drugs, which might affect the results of clinical blood tests. Therefore, future work should strictly distinguish between patients who have been treated and those who have not been treated.

Separation and conversion disorder was a mental illness mainly caused by separation and obvious mental events such as major life events, inner conflict, emotional agitation, suggestion or self-suggestion acting on susceptible individuals. Separation symptoms, also known as hysterical mental symptoms, refer to the partial or complete loss of self-identity recognition and memory of the past and the performance of the scope of consciousness narrowed, selective amnesia or mental outbreak. Conversion symptoms, also known as somatic symptoms of hysteria, refer to the unhappiness of patients when they encounter insoluble problems and conflicts, which manifest in a variety of somatic symptoms. It can appear similar to the symptoms of any disease. It mainly manifests as a variety of somatic symptoms, a narrow range of consciousness, strong suggestive, selective amnesia or emotional outburst and other mental symptoms, but no corresponding organic damage can be found as its pathological basis. This paper collected 12 cases of separation and conversion disorders, although mainly symptoms of separation, but separation and/or conversion obstacles may also appear in the form of conversion disorders, Therefore, attention must be paid to the forms of the disorder, whether it was a separation form or a conversion form; otherwise, it may lead to a wrong conclusion.

In summary, the study revealed the relationship between DBI, APOA1, LDH, ADL, CREA, MON and IL-8 and psychiatric disorders, and further confirmed that these factors can be used to differential diagnosis. Psychotic disorders and affective disorders were two categories that often occur together. Clinically, the two types of disorders were often judged by symptoms, which were prone to mistakes, for example, patients hiding their symptoms or the inadequacy of the attending doctor's subjective judgment. We established a clinical predictive model that included activities of daily living (ADL), biochemical and immune indicators (DBI, APOA1, LDH, CREA, MON and IL-8). In addition, the model established by the decision tree method had the highest predictive power, which provided a reliable basis for future clinical work. Blood test was one of the most commonly used tests in clinic work. From these easy accessed common indicators to build a predictive model, that would reduce the difficulties in the clinic work and make diagnosis more accurate at an early stage.

Declarations

Author contribution statement

Li Wan: Conceived and designed the experiments; Contributed reagents, materials, analysis tools or data.

Xiuyan Liu: Performed the experiments; Wrote the paper.

Xiu Wang: Analyzed and interpreted the data; Wrote the paper.

Chunsong Wen: Contributed reagents, materials, analysis tools or data.

Data availability statement

Data will be made available on request.

Declaration of interest's statement

The authors declare no conflict of interest.

Additional information

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