

CT

1

2

3

1

5

intelligence) : AI 12 (KB, knowledge base) (AI, artificial
criteria) KB (IC, inclusion criteria) (EC, exclusion
가 IC, EC
가 IC
(DD1, 1st-step differentials)
가 [(DD1 IC EC) - (DD1 IC
)]. 10
24 (12 2)
, AI 가
: 280 (IC 214, EC 66) 2
AI
(167 110, $p = 0.0078$)
가가
: AI CT

가 (knowledge domain) CT, CT 가 가 가 , 가 (artificial neural network, ANN) (merge) 가 (1).

가

CT

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2006 3 15

CT

(inheritance)

(tree - in - bud,

TIB) ' 가

가

(3), CT TIB

(2) (knowledge acquisition)

가 (

. knowledge representation)

(reasoning)

TIB

12가

(Table 1).

CT CT

가

(Rule) [-]

a. (Inclusion Criteria) : 가

b. (Exclusion Criteria) : CT

(Fig. 1).

A.

1>

CT

12가

가

CT

F201 (ground - glass opacity) ()

2> F201

Table 1. Description of inheritance, which was exemplified here with Multiple Small Nodules, Daughter Nodules, and Crazy Paving

small nodules	multiple small nodules	centrilobular nodules
small nodules	multiple small nodules	Random nodules
small nodules	multiple small nodules	Many subpleural nodules
small nodules	multiple small nodules	Nodules in relation to large vessels
small nodules	multiple small nodules	Perilymphatic nodules
small nodules	multiple small nodules	
small nodules	daughter nodules	
Ground-glass opacity	crazy-paving	

가 (Fig. 1B).

3> F201 가 (first - step differentials, DD1) (Fig. 1C).

B. 1> DD1 . 2> DD1 (Fig. 1C). , DD1 (F201) . 가

C. B , 가 CT () () . SAS 8.2 ,

D. 가 A - C 가 254 CT , 280 (Table 2) .

	Disease 1	Disease 2	Disease 3	Disease 4
Inclusion Criteria	A B C	D E	F G	A B F
Exclusion Criteria	G	F	A B	E

A

	Disease 1	Disease 2	Disease 4
Inclusion Criteria	A B C	D E	A B F
Exclusion Criteria	G	F	E

B

	Disease 1	Disease 4
Inclusion Criteria	<u>A</u> <u>B</u> C	<u>A</u> <u>B</u> F
Exclusion Criteria	G	E

C

Fig. 1. To explain the inference process, differential diagnosis of 4 diffuse pulmonary diseases is exemplified. Each of letters A-G signifies a clinical or a thin-section CT finding.

A. Inclusion and exclusion criteria list of 4 diffuse pulmonary diseases.

B. After the reader clicked A, the inference engine eliminated disease 3 from the process, since disease 3 had had A in its exclusion criteria list.

C. In the next step, the inference engine eliminated disease 2 as well, since it had not had A in its inclusion criteria list. As a result, the first-step differentials were generated, which include disease 1 and 4. Since A and B (underlined) are common to disease 1 and 4, only C, F, G, E are to be shown to the reader as the new ' finding list ', who then can move on to the second-step differential diagnosis.

Table 2. The Number of Rules Generated for Each Diffuse Pulmonary Disease

Disease Name	Inclusion Criteria	Exclusion Criteria	Total
Lymphangioleiomatosis	10	8	18
Subacute hypersensitivity pneumonitis	15	8	23
Bronchiolitis Obliterans	9	3	12
Pulmonary alveolar proteinosis	11	9	20
Centrilobular emphysema	11	6	17
Hematogenous metastasis	18	7	25
Hydrostatic pulmonary edema	24	6	30
Sarcoidosis	30	2	32
Usual interstitial pneumonia	18	5	23
Bronchogenic spread of pulmonary tuberculosis	24	2	26
Pulmonary lymphangitic carcinomatosis	22	5	27
Bronchiolitis obliterans with organizing pneumonia	22	5	27
Total	214	66	280

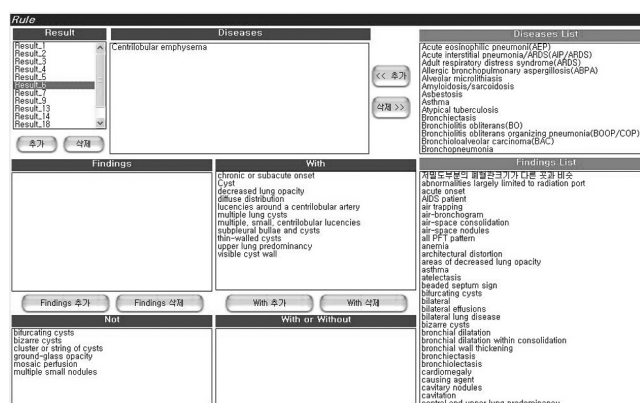


Fig. 2. The ‘ Rule Edit ’ interface is open for editing the knowledge base for centrilobular emphysema. The master user of the program can pick a clinical or thin-section CT finding on the “ Findings List (bottom of right column) ” to add it to either the inclusion (“ With ”, middle of the middle column) or the exclusion criteria list (“ Not ”, bottom of the left column). On the other hand, findings can be removed from IC or EC list if needed. In this picture, “ Findings ” (middle of left column) and “ With and without ” (bottom of the middle column) are also shown, but those functions were abandoned in the development process and are no longer in use.

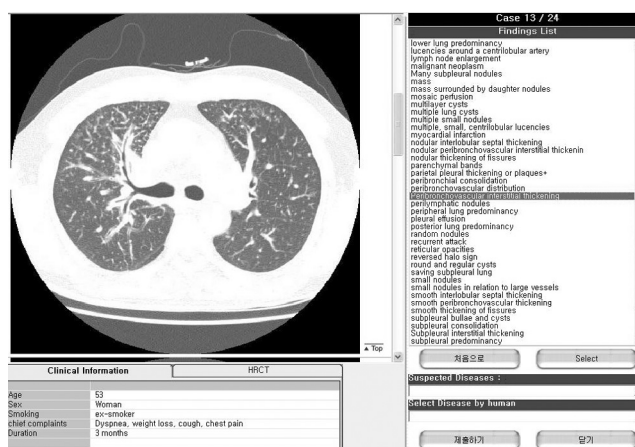


Fig. 3. A case is shown on the left, with the image above and the clinical findings below. The reader has selected a finding (peribronchovascular interstitial thickening), making it highlighted. Now the user is to confirm the selection by clicking the “ Select ” bar (near the bottom of the right column).

‘ Rule Edit ’, ‘ Run ’ 가 가 .
 ‘ Rule Edit ’
 CT
 (Fig. 2).

‘ Run ’ , 24
 가 가
 (Fig. 3)
 가
 (Fig. 4).
 가
 (Fig. 5).
 가
 CT
 Table 3 .
 110

가 167 ($p=0.0078$),

8, 1, 가 (4), 3 (5), (6), X

가 (7),

10 5

, 4 1

(Clinical Decision Supporting System, CDSS)

10 가

가

9

(1).

가

(8).

CT, 가

CT

가

CT 가

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Table 3. Scores for each of the 10 participants who tried to make Differential Diagnosis of 12 Cases with and without the aid of the Artificial Intelligence, respectively

Residency year	4	4	4	3	3	3	3	2	2	2	Total
Score not using Artificial Intelligence	13	16	10	7	12	16	12	11	12	9	110
Score using Artificial Intelligence	23	16	17	19	17	14	20	16	20	14	167

($p = 0.0078$)

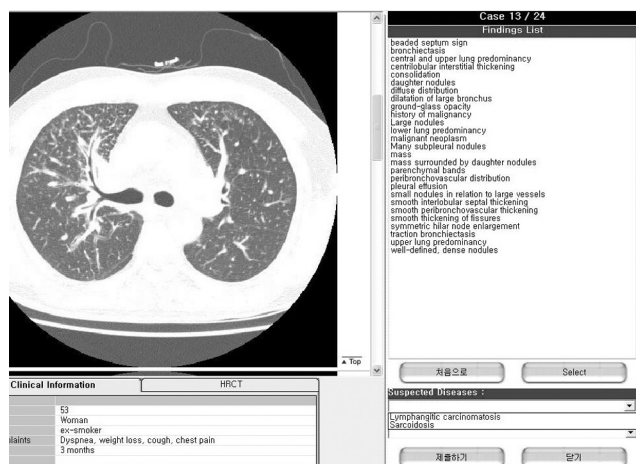


Fig. 4. As a result of inputting “peribronchovascular interstitial thickening” and then “chronic or subacute onset,” a new, shortened list of findings is seen on the right. Note that the number of differentials has been reduced from twelve to two (“Suspected Disease,” bottom of the right column).

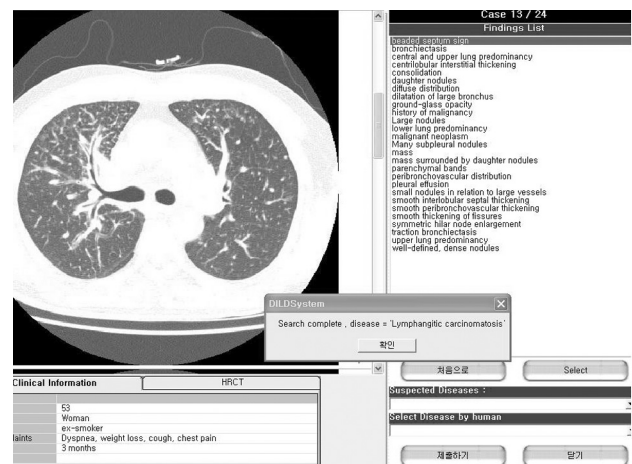


Fig. 5. The system is notifying the reader that the differential process has been completed, with the diagnosis shown in a popup box (right below the image center).

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CT

structure)

가 (tree

(9)

‘tree - in - bud appearance’가

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CADMIUM

[decreased lung

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[decreased lung opacity]

가

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12가

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(arguing)

CADMIUM II

(10). CADMIUM II

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(HRCT
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indeterminate)

. CADMIUM

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Artificial Intelligence Aiding the Thin-section CT Diagnosis of Diffuse Pulmonary Diseases¹

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Purpose: We wanted to develop and test an artificial intelligence (AI) to assist physicians in making the thin-section CT diagnosis of diffuse pulmonary diseases.

Materials and Methods: The AI was composed of knowledge bases (KB) of 12 diffuse pulmonary diseases and an inference engine (IE). The KB of a disease included both the inclusion criteria (IC) and the exclusion criteria (EC), which were the clinical or thin-section CT findings that were known to be present or absent in that particular disease, respectively. From imputing the clinical or thin-section CT findings by the operator who was reading the thin-section CT, AI instantly executed the following two steps. First, the IE eliminated all diseases from the list which the EC had for those particular findings. Next, from a list of remaining diseases, the AI selected those diseases having those findings in its IC to formulate the 1st-step differential diagnosis (DD1). For the differential diagnosis in the next step, the reader could choose one more clinical or thin-section CT finding from the new list: [(all the findings in the IC or EC of DD1) - (the findings in the IC common to all the DD1s)]. The reader could proceed even further if needed. The system was tested on 10 radiology residents who solved 24 problems (two problems for each of 12 diffuse pulmonary diseases) without and then with the aid of the AI. The scores were compared using the Wilcoxon signed rank test.

Results: An AI was made; it was composed of 280 rules (214 IC and 66 EC) and three interfaces (two for program management and another for problem solving). Contestants scored higher ($p = 0.0078$) using the AI (167 vs. 110 respectively), and they responded that they felt that the program was helpful in making decisions.

Conclusion: AI appeared to be helpful in making thin-section CT diagnosis.

Index words : Computed tomography (CT), high-resolution
Lung

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