Original Article

A Predictive Model using Artificial Intelligence on Chest Radiograph in Addition to History and Physical Examination to Diagnose Chronic Obstructive Pulmonary Disease

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Objective: Spirometry is the gold standard for chronic obstructive pulmonary disease (COPD) diagnosis. Some patients are unable to perform spirometry. The study aimed to evaluate the factors associated with COPD and create the predictive model for COPD diagnosis.

Materials and Methods: A cross-sectional study between January 1, 2020, and December 31, 2020, at Srinagarind Hospital included subjects aged ≥40 years who had productive cough or dyspnea >3 months without lung parenchymal disease. Information from history taking, physical examination, chest x-ray (CXR) and spirometry were collected. The stepwise backward multiple logistic regression was performed to evaluate the factors associated with COPD.

Results: One hundred and eight subjects were enrolled; 46 COPD and 62 non-COPD. The independent factors associated with COPD diagnosis were cigarette smoking ≥30 pack-year, body mass index (BMI) <22 kg/m^2, wheezing on forced expiration, modified Medical Research Council Dyspnea Scale (mMRC) ≥2 and emphysema interpreted by AI. The model consisting of these factors showed an area under the receiver operating characteristic curve 0.86 (95% CI, 0.77 to 0.92) for COPD diagnosis. The sensitivity and specificity were 8.7% (95% CI, 2.4 to 20.1%), 100% (95% CI, 94.2 to 100%). The positive predictive value and negative predictive value were 100% (95% CI, 39.8 to 100%), 59.6% (95% CI, 49.5 to 69.1%).

Conclusion: The model consisting of factors including cigarette smoking ≥30 pack-year, BMI <22 kg/m^2, wheezing on forced expiration and presence of emphysema on CXR interpreted by AI had high specificity for COPD diagnosis. The model could be used as a diagnostic tool for those who are unable to perform spirometry.

Keywords: Factors; Model; COPD diagnosis; Artificial intelligence

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Chronic obstructive pulmonary disease (COPD) is a chronic progressive airflow limitation causing by long-term noxious particle exposure. The most important risk factor of COPD development is cigarette smoking[(1)]. The other well-established risk factors are biomass fuel, air pollution, inorganic dust, or organic dust exposure from occupation[(1)]. The global prevalence of COPD from Blanco, et al study conducting in 2019 was 13.1%[(2)]. The prevalence of COPD in central rural Thailand, data from Kitjakrancharoensin studying in 2020, was 5.5%[(3)].

The common symptoms of COPD are chronic cough, dyspnea, or sputum production. The spirometry should be assessed in those who have these respiratory symptoms and/or a history of exposure to noxious particles. Although spirometry is the gold standard for COPD diagnosis, some patients were not suitable to perform spirometry. Underuse or unavailability of spirometry is the most common cause of underdiagnosis, especially in primary care setting[(4)]. Delayed diagnosis of COPD is associated with higher exacerbation, direct cost of health care resource utilization, and mortality[(5)]. Early diagnosis provides an opportunity for early intervention including stop cigarette smoking, initiate pharmacological therapy, and pulmonary rehabilitation. These treatments improve quality of life, reduced the exacerbation and mortality rate of COPD[(1)].

The clinical signs, symptoms, and radiological findings are important factors to establish a presumptive diagnosis. A systematic review of Broekhuizen in 2009 found history and physical examination that was dyspnoea,

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wheezing, previous consultation for wheezing or cough, self-reported COPD, age, smoking, wheezing, forced expiratory time, laryngeal height and prolonged expiration have diagnostic value to diagnose COPD[6]. Another study from Taiwan found that the independent factors associated with COPD diagnosis were age, cigarette smoking, COPD assessment test (CAT) score and peak expiratory flow rate (PEFR). The model consisted of these factors provided high specificity for COPD diagnosis without the use of spirometry[7]. Moreover, chest x-ray (CXR), a widely available test performed in all patients with respiratory symptoms, can be used to aid the diagnosis of COPD by identifying emphysema[8]. Currently, artificial intelligence (AI), a novel technology, has become increasingly interesting. AI can interpret various chest abnormalities including emphysema, fibrosis and cardiomegaly and other thoracic diseases[9-12]. This may assist in diagnosis and reduce the workload of healthcare professionals.

To date, there is no published study about using AI on CXR reading combination with history and physical examination to diagnose COPD, we foresee that the combination above is interesting and could be a valuable COPD diagnostic tool particularly in patients who are not suitable to perform spirometry. The study aimed to create predictive models for COPD diagnosis by adding AI reading on CXR in combination with history taking and physical examination.

Materials and Methods

Study design

A cross-sectional study was conducted between January 1, 2020 to December 31, 2020, at Srinagarind Hospital, Khon Kaen University. The study was approved by the Human Research Ethics Committee, Khon Kaen University (approval number HE621554). All subjects signed consent forms before study enrollment.

Study subjects

The inclusion criteria were subjects aged ≥40 years who presented with a symptom of productive cough or dyspnea for more than 3 months without lung parenchymal disease. All subjects underwent a history taking, physical examination, CXR and spirometry. The exclusion criteria were subjects with a previous history of asthma, bronchiectasis, pulmonary tuberculosis, other chronic respiratory diseases, having a contraindication to performing spirometry and subjects who were suspicious for exacerbation within 6 weeks.

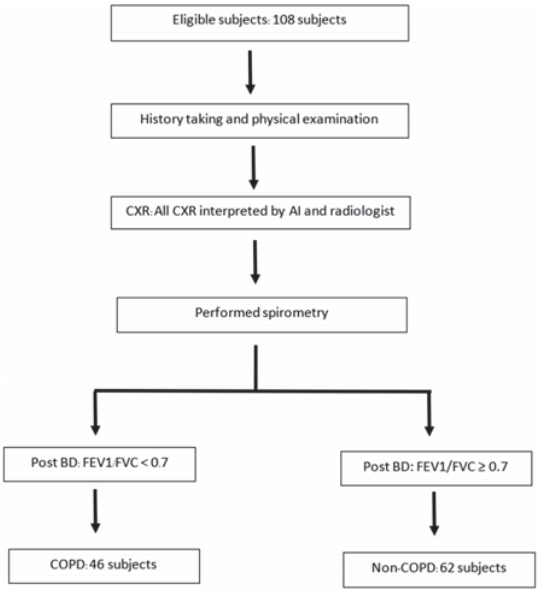
Procedures

All eligible subjects underwent a routine assessment from history taking about symptoms, smoking history, biomass exposure, previous history of pulmonary infection and comorbidities. Moreover, CAT scores and modified Medical Research Council (mMRC) were assessed. Physical examination included body weight, height, laryngeal height, and chest auscultation. CXR and spirometry were done in all subjects on the visiting day. COPD diagnosis was confirmed when post-bronchodilator (BD) forced expiratory volume in 1 second (FEV_1)/forced vital capacity (FVC) less than 0.7 according to GOLD 2019 criteria[1].

The CXR posteroanterior (PA) view was interpreted by a blinded radiologist and AI. A radiologist interpreted the presence of emphysema using any of the following criteria: increased radiolucency of lung fields, hyperinflated lung, flattening of diaphragms, tubular-shaped heart, and pruning of peripheral vasculature[8,13]. The AI program named Inspectra CXR v.1.0 was innovated by Perceptra Co., Ltd., overall accuracy 92% and AUROC of a locally adapted model to diagnose emphysema on Thai CXR dataset was 0.963. The AI program can classify the presence of emphysema into three grades depends on the probability of emphysema presented on CXR[9]. The first grade was emphysema presented less than 30% of CXR, the second grade was 30 to 50% and the third grade was more than 50%. By using this program, this study interpreted the presence of emphysema if the probability of emphysema is more than 30%, or at least grade 2 from AI classification (Figure 1).

Statistical analysis

The sample size was calculated based on the previous study[8], using sample size for cohort study



CXR = chest x-ray; AI = artificial intelligence; BD = broncho-dilator; FEV_1 = Forced expiratory volume in 1 second; FVC = forced vital capacity; COPD = chronic obstructive pulmonary disease; non-COPD = non-chronic obstructive pulmonary disease

Figure 1. Flow chart of study.

equation[14], 104 subjects needed to provide a significance level $\alpha = 0.05$ and 80% power and risk to prevalence ratio 2:1. The categorical data were shown as numbers and percentages. The normal distributed continuous data were presented as mean and standard deviation (SD) while the non-normal distributed data were presented as the median and interquartile range (IQR). A comparison of category data used the Chi-square test and Fisher's exact test depending on data. The nonparametric data used the Mann-Whitney U test for comparison.

The factors associated with COPD diagnosis were evaluated by univariate logistic regression analysis. The stepwise backward multiple logistic regression analysis of factors with p-value <0.2 on univariate analysis or factors with previous reports of clinical significance was performed. Crude odds ratio (cOR) and adjusted odds ratio (aOR) with their 95% confidence intervals (CI) were demonstrated. A p-value of less than 0.05 was considered statistically significant. The predictive model was constructed using the factors independently associated with COPD diagnosis. The properties of the developed models were evaluated with the Akaike information criteria (AIC), area under the receiver operating characteristics curve (AUROC), sensitivity, specificity, positive predictive value (PPV) and negative predictive value (NPV). The data were analyzed using STATA version 10.1 (StataCorp, College Station, Texas).

Results

Between January 1, 2020 to December 31, 2020, one hundred and eight participants were included in the present study. Forty-six subjects were COPD and 62 subjects were non-COPD. Male was 70 subjects (64.8%). The mean (SD) age of subjects was 64.4 (11.0) years. The baseline characteristics were shown in Table 1. The COPD group had a significantly greater proportion of male, cigarette smoking, biomass exposure, a symptom of sputum production, forced expiratory wheezing and older age than in non-COPD group. The COPD group had lower significantly BMI, and laryngeal height.

The median (IQR) of CAT scores was 8 (3 to 13) of COPD and non-COPD of 3 (1 to 9). The CAT score had significantly higher in the COPD group (p=0.002). The mMRC ≥2 was more frequently found in COPD group than in non-COPD group significantly (20 subjects; 43.5% vs. 12 subjects; 19.4%).

The spirometric parameters and radiological findings were shown in Table 2. The presence of emphysema interpreted by the radiologist was 24 subjects (52.2%) of COPD and 17 subjects (27.2%) of non-COPD. The present of emphysema interpreted by AI was 30 subjects (65.2%) of COPD and 22 subjects (35.5%) of non-COPD. The presence of emphysema interpreted by the radiologist and AI significantly higher in the COPD group (p<0.01).

The univariate logistic regression analysis and stepwise backward multiple logistic regression analysis were shown in Table 3. On univariate analysis, the factors significant associated COPD diagnosis were age ≥65 years, BMI <22 kg/m^2, cigarette smoking ≥30 pack-year, biomass exposure ≥10 year, wheezing on forced expiration, laryngeal height ≤4 cm, CAT score ≥7, mMRC ≥2, emphysema on CXR interpreted by AI, emphysema on CXR interpreted by radiologist. According to factors of emphysema interpreted by AI and emphysema interpreted by radiologist were collinearity. Two stepwise backward multivariate logistic regression analysis were conducted. The independent factors of the first analysis were age ≥65 years, BMI <22.0 kg/m^2, cigarette smoking ≥30 pack-year, biomass exposure ≥10 year, wheezing on forced expiration, laryngeal height ≤4 cm, CAT score ≥7, mMRC score ≥2, emphysema interpreted by AI and the independent factors of the second analysis were age ≥65 years, BMI <22.0 kg/m^2, cigarette smoking ≥30 pack-year, biomass exposure ≥10 year, wheezing on forced expiration, laryngeal height ≤4 cm, CAT score ≥7, mMRC score ≥2, emphysema interpreted by radiologist. On stepwise backward multiple logistic regression analysis, the factors significant associated with COPD diagnosis were BMI <22.0 kg/m^2, cigarette smoking ≥30 pack-year, wheezing on forced expiration and mMRC score ≥2.

The three models were created: Model 1, Model 2, and Model 3.

Model 1 consisted of BMI <22 kg/m^2, cigarette smoking ≥30 pack-year, wheezing on forced expiration, mMRC ≥2. The equation of probability of COPD (P_{COPD}) was shown as following:

Logit (P_{COPD}) = -3.20+1.50 BMI <22 kg/m^2 +1.69 cigarette smoking ≥30 pack-year +1.78 wheezing on forced expiration +1.32 mMRC ≥2.

Model 2 consisted of BMI <22 kg/m^2, cigarette smoking ≥30 pack-year, wheezing on forced expiration, mMRC ≥2 and emphysema on CXR interpreted by AI. The equation of probability of COPD (P_{COPD}) was shown as following:

Logit (P_{COPD}) = -3.77+1.38 BMI <22 kg/m^2 +1.56 cigarette smoking ≥30 pack-year +1.85 wheezing on forced expiration +1.53 mMRC ≥2+1.26+ emphysema on CXR interpreted by AI.

Model 3 consisted of BMI <22 kg/m^2, cigarette smoking ≥30 pack-year, wheezing on forced expiration, mMRC ≥2 and emphysema on CXR interpreted by radiologist. The equation of probability of COPD (P_{COPD}) was shown as following:

Logit (P_{COPD}) = -3.45+1.19 BMI <22 kg/m^2 +1.65 cigarette smoking ≥30 pack-year +1.72 wheezing on forced expiration +1.48 mMRC ≥2 +0.90 emphysema on CXR interpreted by radiologist.

The AIC and diagnostic performance of each predictive model were shown in Table 4. The AUROC of each predictive model in COPD diagnosis were shown in Figure 2.

Discussion

Even though spirometry is essential for COPD diagnosis, there is no widely available spirometry in Thailand and some patients cannot perform spirometry. The

Table 1. Characteristics data of study subjects

	COPD n=46	Non-COPD n=62	p-value
Male (n, %)	37 (80.4)	33 (53.2)	<0.01
Age (mean±SD) years	67.8±12.5	61.9±9.5	0.05
BMI (mean±SD) kg/m^2	22.4±4.4	24.4±4.5	0.03
Symptom (n, %)			
Dyspnea	31 (67.4)	35 (56.4)	0.25
Sputum production	28 (60.9)	25 (40.3)	0.03
Dry cough	4 (8.7)	18 (29.0)	0.01
Chest tightness	7 (15.2)	6 (9.7)	0.38
Wheezing	3 (6.5)	7 (11.3)	0.40
Others	2 (4.4)	1 (1.6)	0.57
Duration of symptoms (median (IQR)) months	8.5 (3,24)	12 (4,50)	0.58
Cigarette smoking (n, %)	38 (82.6)	25 (40.3)	<0.01
Current smokers	16 (34.8)	10 (16.1)	0.03
Former smokers	22 (47.8)	15 (24.2)	0.01
Biomass exposure (n, %)	24 (56.2)	20 (32.3)	0.03
Co-morbidities (n, %)			
DM	13 (28.3)	8 (12.9)	0.04
Hypertension	18 (39.1)	27 (43.6)	0.64
Dyslipidemia	6 (13.0)	12 (19.4)	0.38
Cardiovascular disease	7 (15.2)	3 (4.8)	0.06
Allergic rhinitis	2 (4.4)	8 (12.9)	0.12
Others	14 (30.4)	12 (19.3)	0.30
Laryngeal height-cm (mean±SD)	5.35±1.9	6.17±1.7	0.02
Forced expiratory wheezing (n, %)	32 (69.6)	20 (32.3)	<0.01
CAT scores (n, %)			
CAT scores ≥7	27 (58.7)	20 (32.2)	<0.01
mMRC (n, %)			
mMRC 0	11 (23.9)	30 (48.4)	0.01
mMRC 1	15 (32.6)	20 (32.3)	0.96
mMRC 2	12 (26.1)	6 (9.7)	0.02
mMRC 3	7 (15.2)	5 (8.1)	0.24
mMRC 4	1 (2.2)	1 (1.6)	0.83

COPD = chronic obstructive pulmonary disease; non-COPD = non-chronic obstructive pulmonary disease; BMI = body mass index; SD = standard deviation; IQR = interquartile range; DM = diabetes mellitus; AP = anterior posterior

information from history taking, examination and CXR are the simple tools for establishing a presumptive diagnosis. The present study was conducted to create a model to diagnose COPD using those without spirometry. Moreover, we tried to add AI, the innovation which is going to be widespread in near future, to be a part of our model. The study found that independent factors associated with COPD diagnosis were cigarette smoking ≥30 pack-year, BMI <22 kg/m^2, wheezing on forced expiration and presence of emphysema on CXR interpreted by AI. Cigarette smoking is a well-known noxious particle causing COPD. Several reports included cigarette smoking as part of a screening tool for new case COPD findings[15]. Weight loss and cachexia are one systemic consequence of COPD[16]. The possible hypothesis of low BMI may from systemic inflammation[17], non-respiratory muscle atrophy[18,19], increased resting energy expenditure[20]. Previous studies revealed the prevalence of COPD was greater in those with lower BMI[21,22]. Harik-Khan, et al revealed that BMI was inversely associated with COPD development. This study suggested that the

Table 2. Spirometry and radiological findings of study subjects

	COPD n=46	Non-COPD n=62	p-value
Spirometry, post-BD (mean±SD)			
FVC (L)	2.74±0.86	2.74±0.77	0.96
FVC (% predicted)	78.17±21.32	85.98±14.5	0.02
FEV_1 (L)	1.65±0.66	2.08±0.56	<0.01
FEV_1 (% predicted)	68.41±21.21	91.22±16.97	<0.01
FEV_1/FVC	59.34±10.39	86.04±10.14	<0.01
Emphysema on CXR (n, %)			
Radiologist interpretation	24 (52.2)	17 (27.2)	<0.01
AI interpretation	30 (65.2)	22 (35.5)	<0.01

COPD = chronic obstructive pulmonary disease; non-COPD = non-chronic obstructive pulmonary disease; BD = bronchodilator; FVC = forced vital capacity; FEV_1 = forced expiratory volume in 1 second; CAT = COPD assessment test; mMRC = modified Medical Research Council Dyspnea Scale; CXR = chest x-ray; AI = Artificial intelligence

cutoff BMI of 22 kg/m^2 was appropriate to differentiate COPD and non-COPD patients[23], similar to our study. Wheezing is the common finding during acute exacerbation of COPD while less commonly heard during stable COPD. Forced expiratory is the method to enhanced dynamic compression of the airway. Fiz, et al conducted the present study using a contact microphone on the trachea for recording sound during forced expiration. The present study found that wheezing during forced expiration was more recorded in COPD and asthma than healthy subjects[24]. From our study, wheezing on forced expiration was significantly greater in the COPD group. The mMRC is the dyspnea scale. A higher mMRC score indicated more dyspnea. The GOLD guideline suggested mMRC ≥2 in COPD patients need long-acting bronchodilator[1]. To the best of our knowledge, there is no study demonstrating the mMRC associated with COPD diagnosis. From our study, mMRC ≥2 was an independent factor associated with COPD diagnosis.

The study of Casado, et al revealed laryngeal height <4 cm associated with COPD diagnosis[25]. Another study, Mattos, et al revealed laryngeal height <5.5 cm associated with COPD diagnosis[26]. However, our study did not demonstrate the laryngeal height associated with COPD diagnosis. This might be caused by the difference in baseline characteristics of COPD patients. The study of Mattos, et al recruited COPD patients with lower mean FEV_1 which is a more severe degree of airflow obstruction than our study[26]. The CAT score is an 8-item unidimensional to measure health status and assess symptoms of COPD[1]. The study from Taiwan, Kang-Cheng Su, et al conducted a cross-sectional study in order to develop a COPD prediction model to identify undiagnosed at-risk COPD patients. The study demonstrated that age, cigarette smoking, CAT score, peak expiratory flow rate (PEFR) were the factor associated with COPD diagnosis. The CAT score from the present study was weakly associated with COPD by aOR 1.06 (95% CI, 1.00 to 1.12; p=0.037). In the present study, the authors mentioned that the CAT score alone is inadequate as a screening tool for identifying undiagnosed COPD cases. The present study also suggested that CAT ≥7 was the optimal cut-off for COPD diagnosis[7]. From our study, CAT ≥7 is not the independent factor for COPD. This might be CAT score is insensitive to diagnose early COPD as mention in the study from Taiwan[7].

The sensitivity and specificity of CXR for COPD diagnosis were 35% and 87%[27]. Although CXR is insensitive to COPD diagnosis, CXR is a widely available, inexpensive, easy approach. The presence of emphysema on CXR PA view i.e. increased radiolucency of lung fields, hyperinflated lung, flattening of diaphragms, tubular-shaped heart, and pruning of peripheral vasculature helps support COPD diagnosis[13]. Currently AI, computer-aided techniques have been increasingly interested. It has been created for helping diagnosis. AI can reduce the workload of the doctor for CXR interpretation[9]. AI can detect multiple thorax diseases on CXR including emphysema[9-12]. The previous studies showed the sensitivity and specificity of emphysema interpreted by AI were 88 to 94.5% and 90 to 97% respectively[28-30]. The accuracy was 90.0 to 95.4%[28,30] and AUC was 0.985 (95% CI, 0.965 to 0.998)[29]. AI program named Inspectra CXR v.1.0 by Perceptra Co., Ltd. which is a Thai developer funded by The national innovation agency of Thailand (Public Organization) was used in our study. For this program, the performance of emphysema interpretation on CXR was high with AUC 0.963[9]. From our study, the presence of emphysema on CXR interpreted by AI was the independent factor associated with COPD diagnosis.

Spirometry is a procedure measuring the volume of air from the maximal effort of inhalation and exhalation[31]. Spirometry is essential to establish the diagnosis of COPD[1]. This test requires forced expiratory maneuver and well

Table 3. Factors associated with COPD diagnosis

Factors	Univariate analysis			Multivariate analysis					
	cOR	95% CI	p-value	aOR	95% CI	p-value	aOR	95% CI	p-value
Age ≥65 years	2.41	1.10 to 5.26	0.02	-	-	-	2.13	0.79 to 5.74	0.13
BMI <22.0 kg/m^2	2.88	1.25 to 6.61	0.01	3.97[a]	1.27 to 12.38	0.02	3.10[b]	1.08 to 10.20	0.04
Cigarette smoking ≥30 pack-year	4.03	1.89 to 9.80	<0.01	4.77[a]	1.64 to 13.90	<0.01	5.01[b]	1.71 to 14.66	<0.01
Biomass exposure ≥10 year	2.44	1.02 to 5.42	0.02	-	-	-	-	-	-
Family history of COPD	1.68	0.52 to 5.36	0.39	N/A	N/A	N/A	N/A	N/A	N/A
Wheezing on forced expiration	4.80	2.10 to 10.93	<0.01	6.38[a]	2.12 to 19.21	<0.01	5.49[b]	1.85 to 16.30	<0.01
Laryngeal height ≤4 cm	2.44	1.02 to 5.83	0.04	-	-	-	-	-	-
CAT score ≥7	2.98	1.35 to 6.59	<0.01	-	-	-	-	-	-
mMRC score ≥2	3.21	1.36 to 7.56	<0.01	4.60[a]	1.44 to 14.70	0.01	4.25[b]	1.39 to 13.00	0.01
Emphysema interpreted by AI	3.41	1.53 to 7.58	<0.01	3.52[a]	1.27 to 9.76	0.01	N/A	N/A	N/A
Emphysema interpreted by radiologist	2.89	1.29 to 6.45	0.01	N/A	N/A	N/A	2.72	0.93 to 8.00	0.06

[a] = Stepwise backward multiple logistic regression analysis included age ≥65 years, BMI <22.0 kg/m^2, cigarette smoking ≥30 pack-year, biomass exposure ≥10 year, wheezing on forced expiration, laryngeal height ≤4 cm, CAT score ≥7, mMRC score ≥2, emphysema interpreted by AI.
[b] = Stepwise backward multiple logistic regression analysis included age ≥65 years, BMI <22.0 kg/m^2, cigarette smoking ≥30 pack-year, biomass exposure ≥10 year, wheezing on forced expiration, laryngeal height ≤4 cm, CAT score ≥7, mMRC score ≥2, emphysema interpreted by radiologist.
cOR = crude odds ratio; aOR = adjusted odds ratio; BMI = body mass index; kg/m^2 = kilogram per squaremetre; COPD = chronic obstructive pulmonary disease; cm = centrimetre; CAT = COPD assessment test; mMRC = modified Medical Research Council Dyspnea Scale; CXR = chest x-ray; AI = Artificial intelligence

Table 4. Diagnostic performance of each predictive model for COPD diagnosis

	Model 1	Model 2	Model 3
Sensitivity	10.9 (3.6 to 23.6)	8.7 (2.42 to 20.8)	6.5 (1.4 to 17.9)
Specificity	100.0 (94.2 to 100.0)	100.0 (94.2 to 100.0)	100.0 (94.2 to 100.0)
PPV	100.0 (47.8 to 100.0)	100.0 (39.8 to 100.0)	100.0 (29.2 to 100.0)
NPV	60.3 (50.1 to 69.7).	59.6 (49.5 to 69.1)	59.0 (49.0 to 68.5)
AUROC	0.84 (0.77 to 0.92)	0.86 (0.79 to 0.93)	0.85 (0.78 to 0.92)
AIC	113.4	109.1	112.5

CI = confidence interval; PPV = positive predictive value; NPV = negative predictive value; AUROC = area under the receiver operating characteristics curve; AIC = Akaike information criteria
Sensitivity, specificity, NPV, PPV and AUROC were presented as number (95% CI).

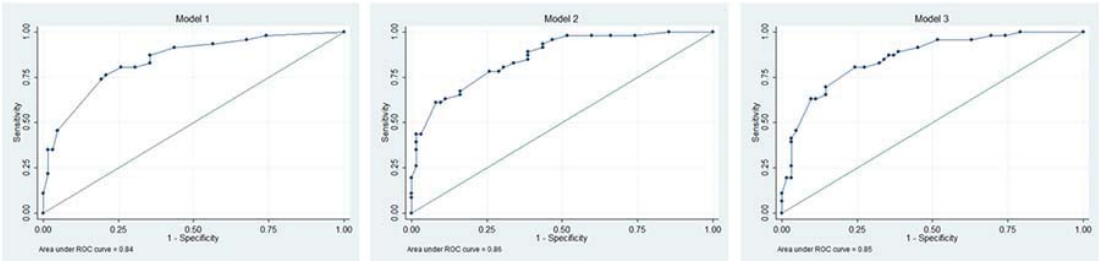


Figure 2. Showed AUROC curves of each predictive model in COPD diagnosis.

cooperation from patients. The patients cannot perform in the patients who had an inability of understanding or unwillingness to directions. Furthermore, some patients have a relative contraindication to perform spirometry including recent myocardial infarction, significant cardiac arrhythmia, uncontrolled pulmonary hypertension, acute cor pulmonale, severe hypertension, unstable pulmonary embolism, history of syncope related to forced expiration or cough, cerebral aneurysm, recent brain surgery, recent eye surgery, active hemoptysis, suspected or active transmissible respiratory infection[31]. From our study, the three models had high specificity for COPD diagnosis. Model 2 included clinical information plus the presence of emphysema on CXR interpreted by AI was the best fit model. Therefore Model 2 is the most appropriate to diagnose COPD in those who are not suitable to perform spirometry.

The strength of our study was that this is the first study that integrated the AI technology to clinical information assisting COPD diagnosis and a few studies evaluating the model for COPD diagnosis.

Our study has some limitations. First, the model needs further study for validation of COPD diagnosis. Second, the model can apply to only patients aged ≥40 years old with the respiratory symptom. The model was unable to apply in asymptomatic patients. Finally, all models were not suitable for using screening in those who suspected COPD according to low sensitivity. The false-negative result could occur.

Conclusion

The factors associated with COPD were cigarette smoking ≥30 pack-year, BMI <22 kg/m^2, wheezing on forced expiration and presence of emphysema on CXR interpreted by AI. Using AI on CXR reading combination with history and physical examination had high performance to diagnose COPD. This model could be used to diagnose COPD instead of spirometry in patients who are unable to perform spirometry.

What is already known on the topic?

COPD should be recognized in those with a chronic respiratory symptoms. The diagnosis of COPD needs spirometry. Some patients are not suitable to perform spirometry. The information from history and physical examination is useful to establish presumptive diagnosis. To date, the model for predicting COPD diagnosis without spirometry is limited.

What this study adds?

The factors associated with COPD diagnosis

were cigarette smoking ≥30 pack-year, BMI <22 kg/m^2, wheezing on forced expiration and presence of emphysema on CXR. Using the model helped diagnose COPD without spirometry.

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Potential conflicts of interest

The authors declare no conflict of interest.

References

1. Global Initiative for Chronic Obstructive Lung Disease. Global strategy for the diagnosis, management, and prevention of chronic obstructive pulmonary disease [Internet]. 2019 [cited 2019 Jan 14]. Available from: https://goldcopd.org/wp-content/uploads/2018/11/GOLD-2019-v1.7-FINAL-14Nov2018-WMS.pdf.
2. Blanco I, Diego I, Bueno P, Casas-Maldonado F, Miravitlles M. Geographic distribution of COPD prevalence in the world displayed by Geographic Information System maps. Eur Respir J 2019;54: 1900610.
3. Kitjakrancharoensin P, Yasan K, Hongyantarachai K, Ratanachokthorani K, Thammasarn J, Kuwuttiwai D, et al. Prevalence and risk factors of chronic obstructive pulmonary disease among agriculturists in a rural community, central Thailand. Int J Chron Obstruct Pulmon Dis 2020;15:2189-98.
4. Lopez-Campos JL, Tan W, Soriano JB. Global burden of COPD. Respirology 2016;21:14-23.
5. Larsson K, Janson C, Stallberg B, Lisspers K, Olsson P, Kostikas K, et al. Impact of COPD diagnosis timing on clinical and economic outcomes: the ARCTIC observational cohort study. Int J Chron Obstruct Pulmon Dis 2019;14:995-1008.
6. Broekhuizen BD, Sachs AP, Oostvogels R, Hoes AW, Verheij TJ, Moons KG. The diagnostic value of history and physical examination for COPD in suspected or known cases: a systematic review. Fam Pract 2009;26: 260-8.
7. Su KC, Ko HK, Chou KT, Hsiao YH, Su VY, Perng DW, et al. An accurate prediction model to identify undiagnosed at-risk patients with COPD: a cross-sectional case-finding study. NPJ Prim Care Respir Med 2019;29:22.
8. Miniati M, Monti S, Stolk J, Mirarchi G, Falaschi F, Rabinovich R, et al. Value of chest radiography in phenotyping chronic obstructive pulmonary disease. Eur Respir J 2008;31:509-15.
9. Chamveha I, Tongdee T, Saiviroonporn P, Chaisangmongkon W. Local adaptation improves accuracy of deep learning model for automated x-ray thoracic disease detection : A Thai study [Internet]. 2020 [cited 2019 Jan 14]: arXiv preprint arXiv:2004.10975. Available from: https://arxiv.org/pdf/2004.10975.pdf.
10. Wang H, Xia Y. ChestNet: A Deep Neural Network for Classification of Thoracic Diseases on Chest Radiography2018 July 01, 2018:[arXiv:1807.03058 p.]. Available from: https://arxiv.org/ftp/arxiv/papers/1807/1807.03058.pdf.
11. Rajpurkar P, Irvin J, Ball RL, Zhu K, Yang B, Mehta H, et al. Deep learning for chest radiograph diagnosis: A retrospective comparison of the CheXNeXt algorithm to practicing radiologists. PLoS Med 2018;15:e1002686.
12. Qin C, Yao D, Shi Y, Song Z. Computer-aided detection in chest radiography based on artificial intelligence: a survey. Biomed Eng Online 2018;17:113.
13. Washko GR. Diagnostic imaging in COPD. Semin Respir Crit Care Med 2010;31:276-85.
14. Fleiss JL. Statistical methods for rates and proportions. Hoboken, NJ: John Wiley & Sons; 1981.
15. Han MK, Steenrod AW, Bacci ED, Leidy NK, Mannino DM, Thomashow BM, et al. Identifying patients with undiagnosed COPD in primary care settings: Insight from screening tools and epidemiologic studies. Chronic Obstr Pulm Dis 2015;2:103-21.
16. Montes de Oca M, Talamo C, Perez-Padilla R, Jardim JR, Muino A, Lopez MV, et al. Chronic obstructive pulmonary disease and body mass index in five Latin America cities: the PLATINO study. Respir Med 2008;102:642-50.
17. Agusti AG. Systemic effects of chronic obstructive pulmonary disease. Proc Am Thorac Soc 2005;2:367-70; discussion 71-2.
18. Wagner PD. Possible mechanisms underlying the development of cachexia in COPD. Eur Respir J 2008;31:492-501.
19. Agusti AG, Sauleda J, Miralles C, Gomez C, Togores B, Sala E, et al. Skeletal muscle apoptosis and weight loss in chronic obstructive pulmonary disease. Am J Respir Crit Care Med 2002;166:485-9.
20. Sergi G, Coin A, Marin S, Vianello A, Manzan A, Peruzza S, et al. Body composition and resting energy expenditure in elderly male patients with chronic obstructive pulmonary disease. Respir Med 2006;100:1918-24.
21. Menezes AM, Perez-Padilla R, Jardim JR, Mui□o A, Lopez MV, Valdivia G, et al. Chronic obstructive pulmonary disease in five Latin American cities (the PLATINO study): a prevalence study. Lancet 2005;366: 1875-81.
22. Zhong N, Wang C, Yao W, Chen P, Kang J, Huang S, et al. Prevalence of chronic obstructive pulmonary disease in China: a large, population-based survey. Am J Respir Crit Care Med 2007;176:753-60.
23. Harik-Khan RI, Fleg JL, Wise RA. Body mass index and the risk of COPD. Chest 2002;121:370-6.
24. Fiz JA, Jane R, Homs A, Izquierdo J, Garcia MA,

Morera J. Detection of wheezing during maximal forced exhalation in patients with obstructed airways. Chest 2002;122:186-91.
25. Casado V, Navarro SM, Alvarez AE, Villafane M, Miranda A, Spaans N. Laryngeal measurements and diagnostic tools for diagnosis of chronic obstructive pulmonary disease. Ann Fam Med 2015;13:49-52.
26. Mattos WL, Signori LG, Borges FK, Bergamin JA, Machado V. Accuracy of clinical examination findings in the diagnosis of COPD. J Bras Pneumol 2009;35:404-8.
27. Pudney E, Doherty M. Plain chest x-ray (CXR) in the diagnosis of chronic obstructive pulmonary disease (COPD). Eur Respir J 2016;48:PA3936.
28. Coppini G, Miniati M, Paterni M, Monti S, Ferdeghini EM. Computer-aided diagnosis of emphysema in COPD patients: neural-network-based analysis of lung shape in digital chest radiographs. Med Eng Phys 2007;29:76-86.
29. Miniati M, Coppini G, Monti S, Bottai M, Paterni M, Ferdeghini EM. Computer-aided recognition of emphysema on digital chest radiography. Eur J Radiol 2011;80:e169-75.
30. Coppini G, Miniati M, Monti S, Paterni M, Favilla R, Ferdeghini EM. A computer-aided diagnosis approach for emphysema recognition in chest radiography. Med Eng Phys 2013;35:63-73.
31. Graham BL, Steenbruggen I, Miller MR, Barjaktarevic IZ, Cooper BG, Hall GL, et al. Standardization of spirometry 2019 update. An Official American Thoracic Society and European Respiratory Society Technical Statement. Am J Respir Crit Care Med 2019;200:e70-88.