

1 **Deep learning-based model for detecting 2019 novel coronavirus pneumonia on**

2 **high-resolution computed tomography: a prospective study**

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45 **Abstract**

46 **Background:** Computed tomography (CT) is the preferred imaging method for diagnosing 2019  
47 novel coronavirus (COVID19) pneumonia. Our research aimed to construct a system based on  
48 deep learning for detecting COVID-19 pneumonia on high resolution CT, relieve working  
49 pressure of radiologists and contribute to the control of the epidemic.

50 **Methods:** For model development and validation, 46,096 anonymous images from 106 admitted  
51 patients, including 51 patients of laboratory confirmed COVID-19 pneumonia and 55 control  
52 patients of other diseases in Renmin Hospital of Wuhan University (Wuhan, Hubei province,  
53 China) were retrospectively collected and processed. Twenty-seven consecutive patients  
54 undergoing CT scans in Feb, 5, 2020 in Renmin Hospital of Wuhan University were prospectively  
55 collected to evaluate and compare the efficiency of radiologists against 2019-CoV pneumonia  
56 with that of the model.

57 **Findings:** The model achieved a per-patient sensitivity of 100%, specificity of 93.55%, accuracy  
58 of 95.24%, PPV of 84.62%, and NPV of 100%; a per-image sensitivity of 94.34%, specificity of  
59 99.16%, accuracy of 98.85%, PPV of 88.37%, and NPV of 99.61% in retrospective dataset. For 28  
60 prospective patients, the model achieved a comparable performance to that of expert radiologist.  
61 With the assistance of the model, the reading time of radiologists was greatly decreased by 65%.

62 **Conclusion:** The deep learning model showed a comparable performance with expert radiologist,  
63 and greatly improve the efficiency of radiologists in clinical practice. It holds great potential to  
64 relieve the pressure of frontline radiologists, improve early diagnosis, isolation and treatment, and  
65 thus contribute to the control of the epidemic.

66 **Keywords:** 2019 novel coronavirus pneumonia, Deep learning, Computed tomography

## 67 **Introduction**

68 In December 2019, a new coronavirus infection disease (hereinafter referred to as COVID-19) was  
69 first reported in Wuhan. Subsequently, the outbreak began to spread widely in China and even  
70 abroad.[1-3]

71 The clinical manifestations of the COVID-19 pneumonia is complicated and could be  
72 characterized as fever, cough, myalgia, headache, and gastrointestinal symptoms onset.[4]  
73 Although the nucleic acid detection was considered determinant for identifying the COVID-19  
74 infection and more rapid detection kit for the novel coronavirus has come into mass production,  
75 computed tomography (CT) scan is still the most efficient modality for detecting and evaluating  
76 the severity of pneumonia.[5] An update series demonstrate that CT findings were positive in all  
77 140 laboratory-confirmed COVID-19 patients, even in the early stage.[4,6] In the fifth version of  
78 diagnostic manual of COVID-19 launched by the National Health and Health Commission of  
79 China, the radiographic characteristics of pneumonia was included the clinical diagnostic standard  
80 in Hubei Province.[7] Subsequently, 14,840 new cases of COVID-19 were reported within one  
81 day on Feb 13, 2020 in Wuhan, including 13332 cases of clinical diagnoses.[8] This highlighted  
82 the importance of CT in the diagnosis of COVID-19 pneumonia.

83 Due to the outbreak of the COVID-19, thousands of patients waited in line for CT  
84 examination in the designated fever outpatient hospital at Wuhan and other cities. As of Feb 14,  
85 there are 5,534 suspected cases, 38,107 confirmed patients receiving treatment in hospital, and  
86 77,323 cases under medical observation in Hubei province.[9] Most of them need to undergo CT  
87 examination, however, there are less than 4,500 radiologists in cities of Hubei according to the  
88 China Health Statistical Yearbook (2018).[10] Meanwhile, because the lung infection foci are

89 small in the early stage of the COVID-19 infection, thinner layer (2.5mm, 1.25mm or even  
90 0.625mm) scanning were usually needed instead of conventional CT scan (5 mm) for diagnosis,  
91 which would be more time-consuming. All these made radiologists overloaded, delay the  
92 diagnosis and isolation of patients, affect patient's treatment and prognosis, and ultimately, affect  
93 the control of COVID-19 epidemic.

94 Deep learning, an important breakthrough in the domain of AI in the past decade, has huge  
95 potential at extracting tiny features in image analysis.[11] Our group also succeeded in recruiting  
96 this technique in minor lesion detection and real-time assistance to doctors in gastrointestinal  
97 endoscopy.[12-16]

98 In the present research, we construct and validate a system based on deep learning for  
99 identification of viral pneumonia on CT. Our model has comparable performance with expert  
100 radiologist, but take much less time.

101

## 102 **Method**

### 103 **Patients**

104 We first retrospectively collected 46,096 anonymous images from 106 admitted patients, including  
105 51 patients of laboratory confirmed COVID-19 pneumonia and 55 control patients of other  
106 diseases in Renmin Hospital of Wuhan University (Wuhan, Hubei province, China) for model  
107 development. The patients' CT scan images and reports, history, clinical manifestations, physical  
108 findings, and viral pathogen results were all collected. For prospective patients, 27 consecutive  
109 patients undergoing CT scans were enrolled in the designated CT rooms in Feb 5, 2020 in Renmin  
110 Hospital of Wuhan University.

111 This study was approved by the Ethics Committee of Renmin Hospital of Wuhan University.  
112 Written informed consent was provided by all prospective participants. Because of virus  
113 contamination, the signed informed consents were carefully sealed and kept in the specific place  
114 according to the Law of the People's Republic of China on Infectious Disease Prevention and  
115 Control.[17] For patients whose CT scans were stored in the retrospective databases, informed  
116 consent was waived by the Ethics Committee.

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### 118 **Diagnostic testing for COVID-19**

119 Patient's respiratory secretions were collected and transferred to a sterile test tube with a virus  
120 transport medium. Fluorescent RT-PCR analysis of samples was performed using the COVID-19  
121 nucleic acid detection kit developed by Shanghai GeneoDx Biotechnology Co., Ltd. This detection  
122 kit was approved by the US National Drug Administration (NMPA) on January 26, 2019 and  
123 recommended by the Centers for Disease Control and Prevention (CDC).[18] The rapid,  
124 high-precision COVID-19 detection kit greatly accelerated the confirmation of human COVID-19  
125 infection.

126

### 127 **Datasets**

128 As shown in **Figure 1**, a total of 46,096 CT scan images from 51 COVID-19 pneumonia patients  
129 and 55 control patients of other disease were collected for developing the model to detect  
130 COVID-19 pneumonia. After filtering those images without good lung fields, 35355 images were  
131 selected and split into training and retrospectively testing datasets. Enrolled images in training  
132 dataset covered almost all common CT features of COVID19 pneumonia, as presented in **Figure 2**.

133 Three radiologists with more than 5 years of clinical experience labelled infection lesions of  
134 COVID-19 pneumonia patients in training dataset, and selected images containing COVID19  
135 pneumonia lesions in testing set, and their labels were combined by consensus. For prospectively  
136 testing the model, 13,911 images of 27 consecutive patients undergoing CT scans in Feb 5, 2020  
137 in Renmin Hospital of Wuhan University were further collected. All CT scans were obtained in  
138 Renmin Hospital of Wuhan University. The instruments used in this study included Optima CT680,  
139 Revolution CT and Bright Speed CT scanner (all GE Healthcare).

140

#### 141 **Training algorithm**

142 UNet++, a novel and powerful architecture for medical image segmentation was implemented to  
143 develop the model.[19,20] We first trained UNet++ to extract valid areas in CT images using 289  
144 randomly selected CT images and tested it in other 600 randomly selected CT images. The  
145 training images were labelled with the smallest rectangle containing all valid areas by researchers.  
146 The model successfully extracted valid areas in 600 images in testing set with an accuracy of  
147 100%. For detecting suspicious lesions on CT scans, 691 images of COVID-19 pneumonia  
148 infection lesions labelled by radiologists and 300 images randomly selected from patients of  
149 non-COVID-19 pneumonia were used. Taking the raw CT scan images as input with a resolution  
150 of 512×512, and the labelled map from the expert as output, UNet++ was used to train in Keras in  
151 an image-to-image manner. The suspicious region was predicted under a confidence cutoff value  
152 of 0.50, and a prediction box pixel of over 25. The training curves of UNet++ for extracting valid  
153 areas and detecting suspicious lesions in CT images were shown in **Supplementary Figure 1** and  
154 **Supplementary Figure 2**, respectively. The prediction schematic of the model was shown in

155 **Figure 3.** Raw images were firstly input into the model, and after processing of the model,  
156 prediction boxes framing suspicious lesions were output. Valid areas were further extracted and  
157 unnecessary fields were filter out to avoid possible false positives. To predict by case, a logic  
158 linking the prediction results of consecutive images was added. CT images with the above  
159 prediction results were divided into four quadrants, and results would be output only when three  
160 consecutive images were predicted to have lesions in the same quadrant.

161

### 162 **Testing of the model in retrospective data**

163 To evaluate the performance of the model on CT scan images, five metrics including the accuracy,  
164 sensitivity, specificity, PPV and NPV were calculated as follows: accuracy = true predictions/total  
165 number of cases, sensitivity = true positive/positive, specificity = true negative/negative, positive  
166 prediction value (PPV) = true positive/(true positive + false positive), negative prediction value  
167 (NPV) = true negative/(true negative + false negative). The “true positive” is the number of  
168 correctly predicted COVID-19 pneumonia cases/images, “false positive” is the number of  
169 mistakenly predicted COVID-19 pneumonia cases/images, “positive” is the number of  
170 cases/images of COVID-19 pneumonia patients, “true negative” is the number of correctly  
171 predicted non-COVID-19 pneumonia cases/images, “false negative” is the number of mistakenly  
172 predicted non-COVID-19 pneumonia cases/images and ‘negative’ is the number of  
173 non-COVID-19 pneumonia cases/images enrolled. For image-based metrics, 636 images  
174 containing infection lesions identified by radiologists among 11 patients of COVID-19 pneumonia  
175 were used as the positive sample, and 9369 CT scan images from 31 patients of non-COVID-19  
176 pneumonia were used as the negative sample.



177 **Evaluating the efficiency of radiologist in traditional way**

178 To evaluate the performance and cost of time of radiologist against 2019-CoV pneumonia,  
179 prospectively consecutive patients undergoing CT scans were enrolled in the designated CT rooms  
180 in Feb 5, 2020 in Renmin Hospital of Wuhan University. An expert radiologist was required to  
181 read all CT images of enrolled patients using the working computer, and determine if each patient  
182 has viral pneumonia. The research assistant used a stopwatch to record the expert's reading time.  
183 The expert radiologist was associate chief physician of the Radiology Department of Renmin  
184 Hospital of Wuhan University, with clinical experience of 30 years, and independently diagnosed  
185 about 300 viral pneumonia. Hospitalized viral pneumonia cases judged by radiologists were all  
186 diagnosed using COVID-19 nucleic acid detection kit to confirm COVID-19 infection. The  
187 computed radiography imaging system used by the radiologist was VisionPACS (Intechhosun,  
188 Beijing, China).

189

190 **Comparison between the model and radiologist in prospective data**

191 The CT scan images of the prospective patients as above were collected and imported into the  
192 model for prediction. The model's performance and cost of time were compared with that of the  
193 expert radiologist. Inconsistent results between the expert and model were reviewed by three  
194 radiologists, including the expert and other two radiologists, senior staff members of the  
195 Radiology Department of Renmin Hospital of Wuhan University, with clinical experience about  
196 10 years, and independently diagnosed about 150 viral pneumonia.

197

198 **Evaluating the efficiency of radiologist with the assistance of AI**

199 To evaluate the performance and cost of time of radiologist against 2019-CoV pneumonia with the  
200 assistance of our model, the prediction results of the model (whether a patient has viral pneumonia,  
201 and labels marking lesions) were copied to the working computer in the designated CT rooms.  
202 After 10 days of wash out period (in Feb 16, 2020), the same expert radiologist was required to  
203 re-read all CT images of 27 prospective patients using the working computer where results of the  
204 model could be viewed, and determine if each patient has viral pneumonia. The research assistant  
205 used a stopwatch to record the expert's reading time again. Hospitalized viral pneumonia cases  
206 judged by radiologists were all diagnosed using COVID-19 nucleic acid detection kit to confirm  
207 COVID-19 infection. The computed radiography imaging system used by the radiologist was  
208 VisionPACS (Intechhosun, Beijing, China).

209

#### 210 **Statistical analysis**

211 A two-tailed paired Student's t test with a significance level of 0.05 was used to compare  
212 differences in the cost time of the model and radiologist.

213

#### 214 **Role of the funding sources**

215 The funder of the study had no role in study design, data collection, data analysis, data  
216 interpretation, or writing of the report. The corresponding author had full access to all the data in  
217 the study and had final responsibility for the decision to submit for publication.

218

## 219 **RESULTS**

### 220 **Patients**

221 The baseline characteristics and CT findings of 51 patients of 2019-CoV pneumonia and 55  
222 control patients in retrospective dataset were shown in **Table 1** and **Table 2**, respectively. Baseline  
223 characteristics were comparable between training and testing datasets. The 31 control patients in  
224 retrospective testing dataset include 2 lung cancer, 4 tuberculosis, 2 bronchiectasis, 2 nonviral  
225 pneumonia, 1 lung bullae and 20 with no obvious finding in CT scan.

226

227 **Table 1.** Clinical characteristics of enrolled patients of COVID19 pneumonia

	All patients (n=51)	Training set (n=40)	Testing set (n=11)
Age, years, median (IQR)	52 (38, 69)	54.5 (41.5, 71.25)	42 (34.5, 65.5)
Sex, n (%)			
Men	18 (35.3)	11 (27.5)	7 (63.6)
Women	33 (64.7)	29 (72.5)	4 (36.4)
Presenting symptoms and signs onset, n (%)			
fever	28 (54.9)	21 (52.5)	7 (63.6)
cough	27 (52.9)	20 (50)	7 (63.6)
Chest tightness or pain	7 (13.7)	6 (15)	1 (9.1)
dyspnea	6 (11.8)	6 (15)	0
Muscle soreness	10 (19.6)	8 (20)	2 (18.2)
Expectoration	12 (23.5)	10 (25)	2 (18.2)
Headache	3 (5.9)	2 (5)	1 (9.1)
Digestive symptoms	6 (11.8)	6 (15)	0
CT findings, n (%)			
Unilateral pneumonia	18 (35.3)	13 (30)	5 (45.5)
bilateral pneumonia	33 (64.7)	27 (70)	6 (54.5)
Multiple mottling and ground-glass opacity	16 (31.4)	13 (32.5)	3 (27.3)

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233 **Table 2.** Clinical characteristics of enrolled control patients.

	All patients (n=55)	Training set (n=24)	Testing set (n=31)
Age, years, median (IQR)	48(34.5, 55)	50.5 (38.25, 55.25)	47 (34.5, 54.5)
Sex, n (%)			
Men	31 ( 56.36 )	12 (50)	19 (61.29)
Women	24 ( 43.64 )	12 (50)	12 (38.71)
CT examination indications, n (%)			
Viral pneumonia to be discharged	7 ( 12.73 )	0 ( 0 )	1 ( 3.23 )
Pulmonary bullae to be discharged	2 ( 3.64 )	2 ( 8.33 )	0 ( 0 )
Tuberculosis	1 ( 1.82 )	1 ( 4.17 )	0 ( 0 )
Lower respiratory infection	3 ( 5.45 )	1 ( 4.17 )	2 ( 6.45 )
Metastatic lung tumor to be discharged	7 ( 12.7 )	5 ( 20.83 )	2 ( 6.45 )
Routine examination before admission	41 ( 74.55 )	15 ( 62.5 )	26 ( 83.87 )
CT findings, n (%)			
No obvious abnormality	44 ( 80 )	24	20 ( 64.52 )
Tuberculous lesion	4 ( 7.27 )	--	4 ( 12.90 )
Suspected neoplastic lesions	2 ( 3.64 )	--	2 ( 6.45 )
Inflammatory lesions (non-viral)	2 ( 3.64 )	--	2 ( 6.45 )
Bronchiectasia	2 ( 3.64 )	--	2 ( 6.45 )
Bullae of lung	1 ( 1.82 )	--	1 ( 3.23 )

234

235 **The performance of the model on retrospective dataset**

236 Among 4382 CT images from 11 patients of COVID-19 pneumonia and 9369 images from 31

237 control patients, the model correctly diagnosed the patients with a per-patient sensitivity of 100%,

238 specificity of 93.55%, accuracy of 95.24%, PPV of 84.62%, and NPV of 100%. A per-image

239 sensitivity of 94.34%, specificity of 99.16%, accuracy of 98.85%, PPV of 88.37%, and NPV of

240 99.61%. Representative images predicted by the model were shown in **Figure 4**.

241

242 **The performance of the model in consecutive prospective patients**

243 Twenty-seven patients were enrolled in the prospective dataset. Sixteen (59.26%) patients were

244 diagnosed as viral pneumonia by the expert radiologist, and the other eleven patients were not.  
245 Two other radiologists reviewed the CT imaging, approved the expert's results, and summarized  
246 that the CT characteristics of the 11 patients not diagnosed by the expert include 5 ground glass  
247 nodules, 3 diminutive nodules, 2 normal and 1 fibrosclerosis.

248 The model successfully detected all the 16 patients of viral pneumonia diagnosed by the  
249 expert. Among the other 11 patients, 2 were also detected by the model. The predictions in one  
250 case was fibrosclerosis lesion, and the other one was normal stomach bubble. Using results of the  
251 radiologists as the gold standard, the model achieved a per-patient sensitivity of 100%, accuracy  
252 of 92.59%, specificity of 81.82%, PPV of 88.89% and NPV of 100% in the 27 prospective patients.  
253 Among the 16 patients diagnosed as viral pneumonia by radiologists, 8 admitted patients were  
254 confirmed as COVID-19 infection, and the others were outpatients that difficult to follow nucleic  
255 acid results. The average prediction time for model was 41.34s per patient (IQR 39.76-44.48). The  
256 performance of the model on detecting COVID-19 pneumonia was shown in **Table 3**.

257  
258 **Table 3.** The performance of the deep learning model on both retrospective and prospective  
259 dataset

	Sensitivity	Specificity	Accuracy	PPV	NPV
Retrospective testing					
Per patient	100%	93.55%	95.24%	84.62%	100%
Per image	94.34%	99.16%	98.85%	88.37%	99.61%
Prospective testing (Per patient)	100%	81.82%	92.59%	88.89%	100%

260 \*PPV: positive prediction value, NPV, negative prediction value.

261

### 262 **Comparison between the efficiency of radiologist with or without the assistance of AI**

263 In the first time the expert radiologist read CT scan images of the 27 prospective patients, the

264 average reading time for him to determine whether each patient has viral pneumonia was 116.12s  
265 per case (IQR 85.69-118.17). After 10 days of wash out period, the same expert radiologist re-read  
266 the CT images of the 27 prospective patients with the assistance of the AI model. The results for  
267 determining whether each patient has viral pneumonia were not changed, while the average  
268 reading time of the expert was greatly decreased by 65%. This indicates that the efficiency of  
269 radiologist could be greatly improved with the assistance of AI.

270 A website has been made available to provide free access to the present model  
271 (<http://121.40.75.149/znyx-ncov/index>) (Figure 5). CT scan images could be uploaded by both  
272 clinicians and researches as a second opinion consulting service, especially in other provinces or  
273 countries unfamiliar with the radiologic characteristics of COVID-19. Cases of COVID-19  
274 pneumonia were also been made available on the open-access website, which might be a useful  
275 resource for radiologists and researchers for fighting COVID-19 pneumonia.

276

## 277 **DISCUSSION**

278 As of Feb 14, 2020, the national health commission had reported 66,492 confirmed cases,  
279 1,523 deaths and 8,969 suspected cases.[21] In the face of such large number of patients and high  
280 contagiosity of the novel coronavirus (with an estimated reproduction number  $R_0$  of 2.2~6.47),  
281 timely diagnosis and isolation are the keys to prevent further spread of the virus.[22-26] CT scan  
282 is the most efficient modality for screening and clinically diagnosing COVID-19 pneumonia.[5,7]  
283 However, compared to the needs of the patients, the number of radiologists is quite small,  
284 especially in Hubei province, China, which could greatly delay the diagnosis and isolation of  
285 patients, affect patient's treatment and prognosis, and ultimately, affect the overall control of

286 COVID-19 epidemic.

287 Deep learning, a technology has shown great performance on extracting tiny features in  
288 radiology data, may hold the promise to alleviate this problem.[11] Recently, Ardila D, et al  
289 achieved end-to-end lung cancer screening on low-dose chest CT with an AUC of 94.4%.[27]  
290 Chae KJ, et al successfully used the convolutional neural network to classify small ( $\leq 2$  cm)  
291 pulmonary nodules on CT scan images.[28] However, there was rare research being conducted to  
292 detect viral pneumonia.[11,27,28] In previous work, our group succeeded in recruiting deep  
293 learning in minor lesion detection and real-time assistance to doctors in gastrointestinal  
294 endoscopy.[12-16] Here, we enrolled this technique in identification of COVID-19 pneumonia in  
295 CT images. Results from both retrospective and prospective patients showed that the model was  
296 comparable to the level of expert radiologist, and hold great potential to reduce diagnosing time.  
297 **(Figure 6)**

298 Early diagnosis and early isolation of suspected patients are the most important ways to  
299 prevent the spread of epidemic.<sup>19</sup> Due to the sudden outbreak of COVID19, the radiology  
300 department is overloaded and patients have to wait for long times for chest CT scan, which largely  
301 increase the risk of cross-infection. In recent days, radiologists' daily workload is huge in Hubei  
302 province, and a CT scan report has to be awaited several hours to achieve. Based on the number of  
303 suspected patients and close contacts in being, radiologists in the hardest hit, Hubei province,  
304 China, may not be enough to resist the rapid spread of the virus, which holds high estimated R0 of  
305 2.2~6.47.[23-26] It could be inferred that before radiologists fulfilling the demands of existing  
306 patients, newly infected cases would appear, and the overall burden of radiologists is more  
307 overwhelming like a growing snowball. Relieving the pressure of radiologists is essential for the

308 control of virus spreading. In the present study, our model achieved a comparable performance but  
309 with much shorter time compared with expert radiologists. It holds great potential to relieve the  
310 pressure of radiologists in clinical practice, and contribute to the control of the epidemic.

311 Timely diagnosis and early treatment of infected patients is important for patients'  
312 prognosis.[29] The fatality rate of COVID19 patients in Hubei province is significantly higher  
313 than that of other regions, which probably due to delayed treatment and shortage of medical  
314 resources.[8,30] Accelerating diagnosis efficiency is significant for improving patient outcomes.  
315 In the present study, our model helped expert radiologists achieve the same work with much  
316 shorter time, which greatly accelerats the efficiency of diagnosis in clinical practice, and may  
317 contribute to the improvement of patient outcome.

318 In addition to relieving radiologists' pressure and accelerating diagnosis efficiency, artificial  
319 intelligence also holds the potential to reduce miss diagnosis of COVID-19 patients. The lung  
320 infection foci are sometimes mild in the early stage of the COVID-19 infection,<sup>5</sup> and requires  
321 careful observation under 0.625mm layer scanning. Radiologists vary in skills, and could be  
322 affected by subjective status and outside pressure. One miss diagnosis could lead to multiple  
323 spread. The model is highly sensitive and stable, and would never be affected by work burden and  
324 work time. As a preliminary screening tool, it might help radiologists improve the sensitivity and  
325 reduce miss diagnosis.

326 On the basis of the accuracy and efficiency of the model in detecting COVID-19 pneumonia,  
327 a cloud-based open-access artificial intelligence platform was constructed to provide assistance for  
328 detecting COVID-19 pneumonia worldwide. CT scan images could be uploaded freely by both  
329 clinicians and researches as an assistant tool, especially in other provinces or countries unfamiliar



330 with the radiologic characteristics of COVID-19. This free open-access website can read images in  
331 batches, provide high-level auxiliary diagnostic services for different hospitals in free, and expand  
332 the boundaries of regions and manpower. Cases of COVID-19 pneumonia were also been made  
333 available on the open-access website, which might be a useful resource for radiologists and  
334 researchers for fighting COVID-19 pneumonia.

335 In summary, the deep learning-based model achieved a comparable performance with expert  
336 radiologist using much shorter time. It holds great potential to improve the efficiency of diagnosis,  
337 relieve the pressure of frontline radiologists, accelerates the diagnosis, isolation and treatment of  
338 COVID19 patients, and therefore contribute to the control of the epidemic.

339

#### 340 **AUTHORS' CONTRIBUTIONS**

341 YH and YL conceived and supervised the overall study. WL and GD contributed to writing of the  
342 manuscript. YH, YL, HS and WY contributed to critical revision of the report. CJ, ZL, ZJ, GD,  
343 WH, DZ, XY, ZY and CX contributed to collecting and analyzing the data of patients. CJ, ZL and  
344 ZY contributed to label CT images. HS, HX, ZB, ZK and WY developed the system. All authors  
345 reviewed and approved the final version of the manuscript.

346

#### 347 **CONFLICT OF INTEREST**

348 Wuhan EndoAngel Medical Technology Company collaborated in this study. Shan Hu, Xiao Hu,  
349 Biqing Zheng, Kuo Zhang are research staffs of Wuhan EndoAngel Medical Technology  
350 Company. All authors declared no conflict of interest.

351

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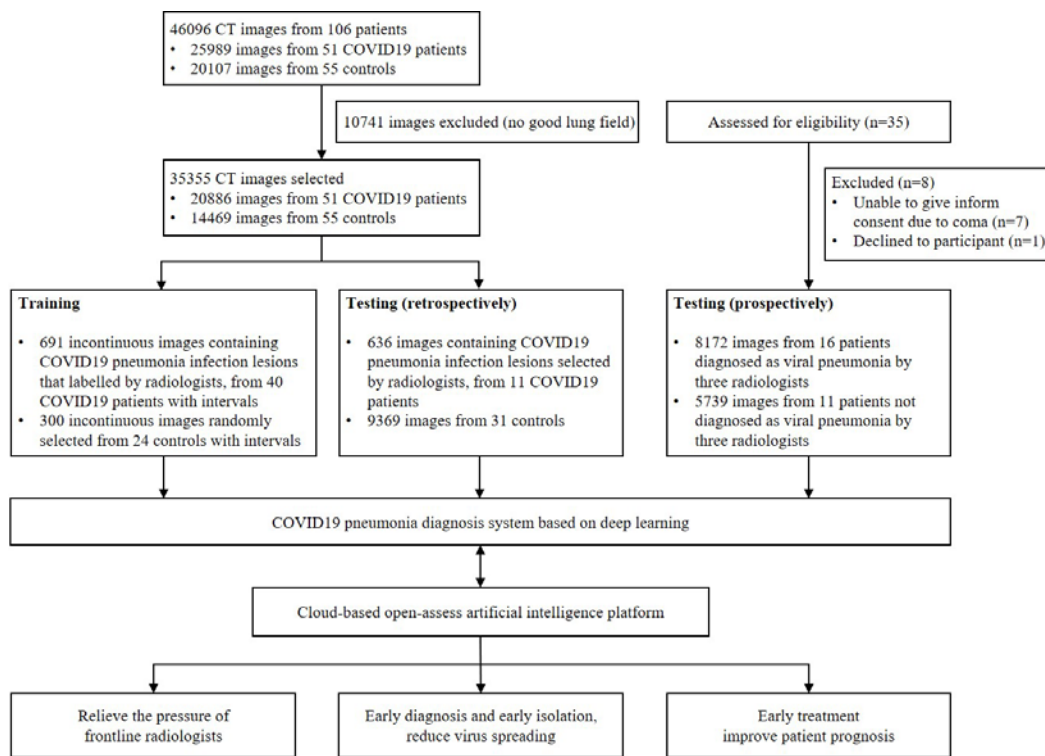
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441 **FIGURES**

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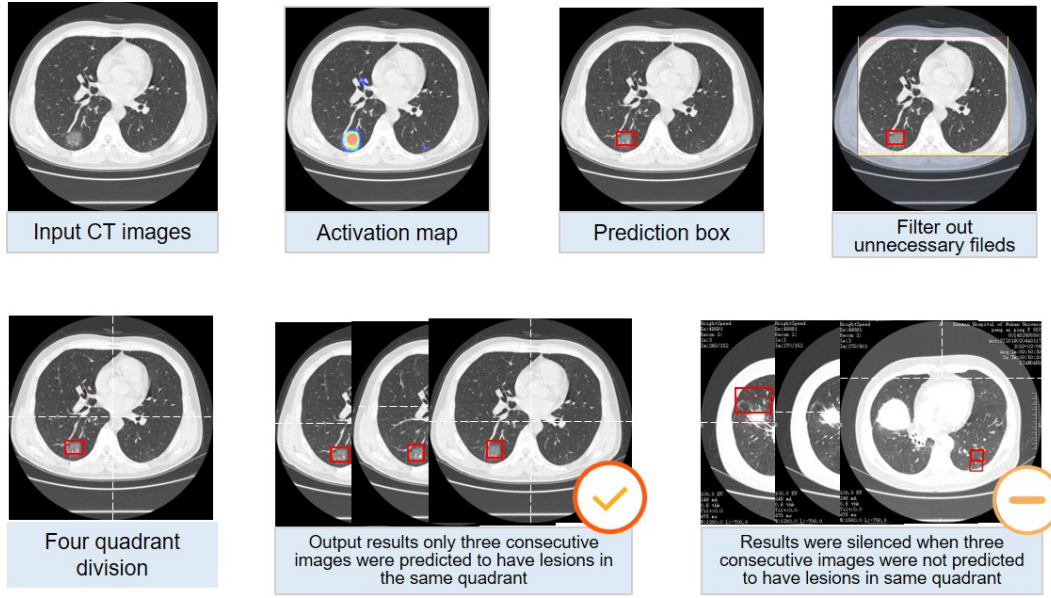
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444 **Figure 1. Workflow diagram for the development and evaluation of the model for detecting**

445 **COVID19 pneumonia.**

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449 **Figure 2. Representative images of COVID19 pneumonia.** More than six common Computed

450 tomography (CT) features of COVID19 pneumonia were covered in selected images. 1a-1d, the

451 lesions were mainly ground-glass-like, with thickened blood vessels walking and including

452 gas-bronchial signs in 1c; 2a-2d, the lesions were mainly ground glass changes, and paving

453 stone-like changes were observed on 2d; 3a-3c, the lesions become solid with a large range, and

454 air-bronchial signs are seen inside; 4, the lesion is located in the lower lobe of both lungs, and is

455 mainly grid-like change with ground glass lesion; 5a-5b, the lesions are mainly consolidation;

456 6a-6b, the lesions are mainly large ground glass shadows, showing white lung-like changes, with

457 air-bronchial signs.

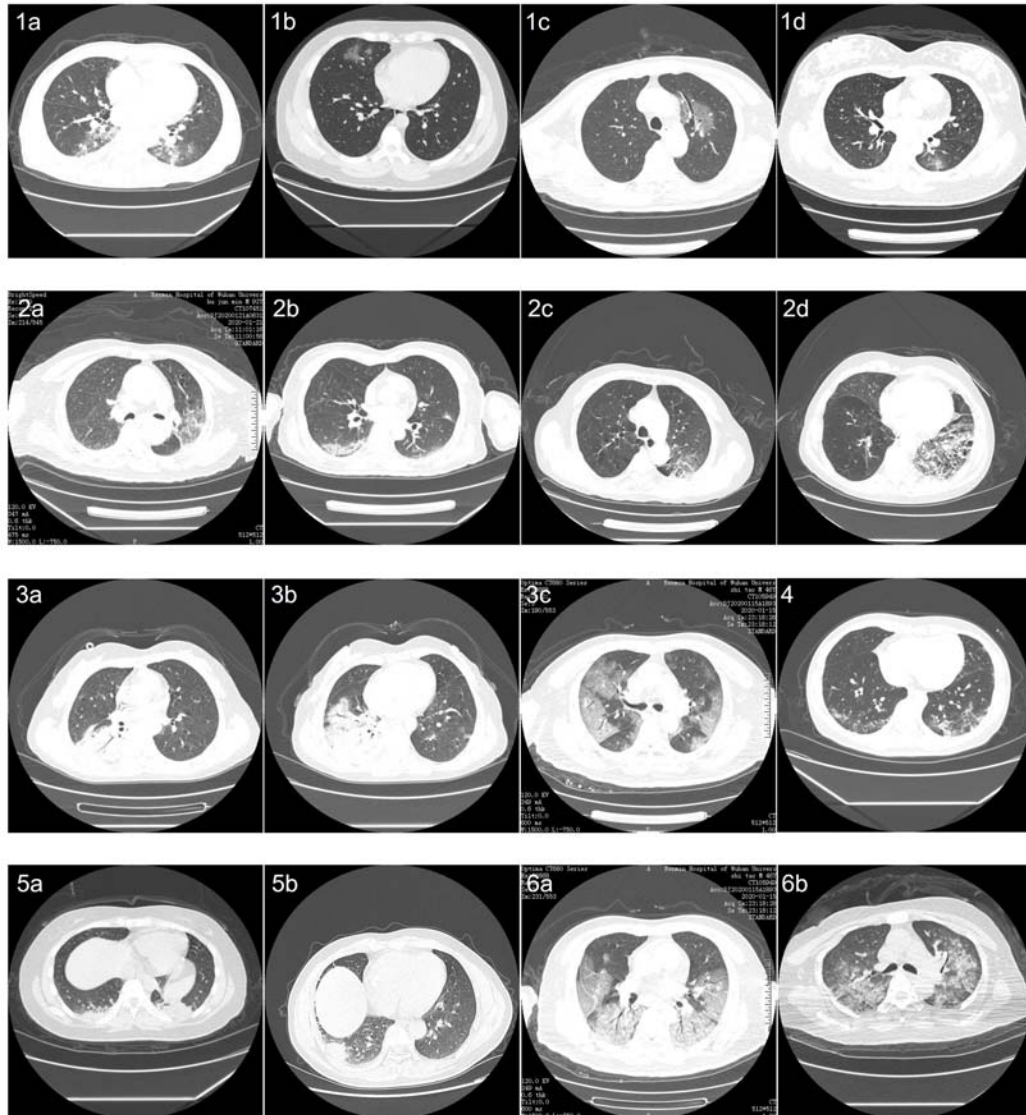
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464 **Figure 3. Processing and prediction schematic of the model.** Raw images were firstly input into

465 the model, and after processing of the model, prediction boxes framing suspicious lesions were

466 output. Valid areas were further extracted and unnecessary fields were filter out to avoid possible

467 false positives. To predict by case, a logic linking the prediction results of consecutive images was

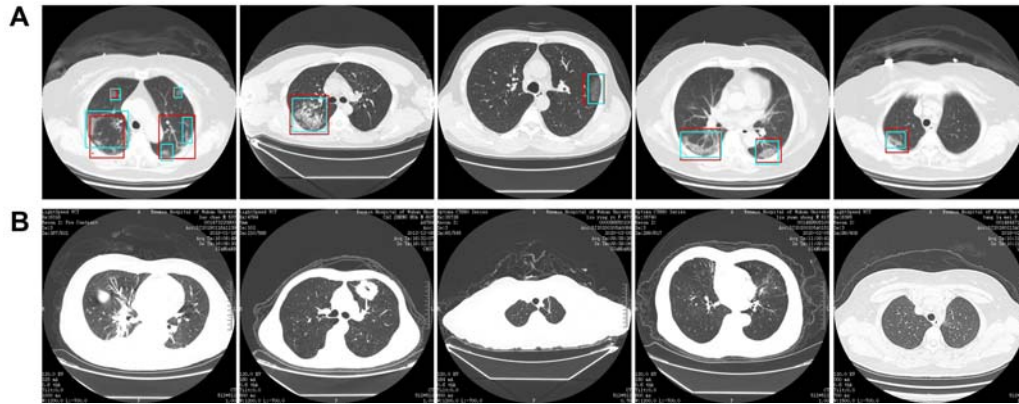
468 added. Computed tomography (CT) images with the above prediction results were divided into

469 four quadrants, and results would be output only when three consecutive images were predicted to

470 have lesions in the same quadrant.

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473 **Figure 4. Representative images of the model's predictions.** A. Computed tomography (CT)

474 images of COVID19 pneumonia. The predictions between the artificial intelligence model and

475 radiologists were consistent. Green boxes, labels from radiologists; red boxes, labels from the

476 model. B. CT images of the control. The first image is an ordinary bacterial pneumonia, showing a

477 consolidation of the right lower lobe. The second image has a tumorous lesion in the lung,

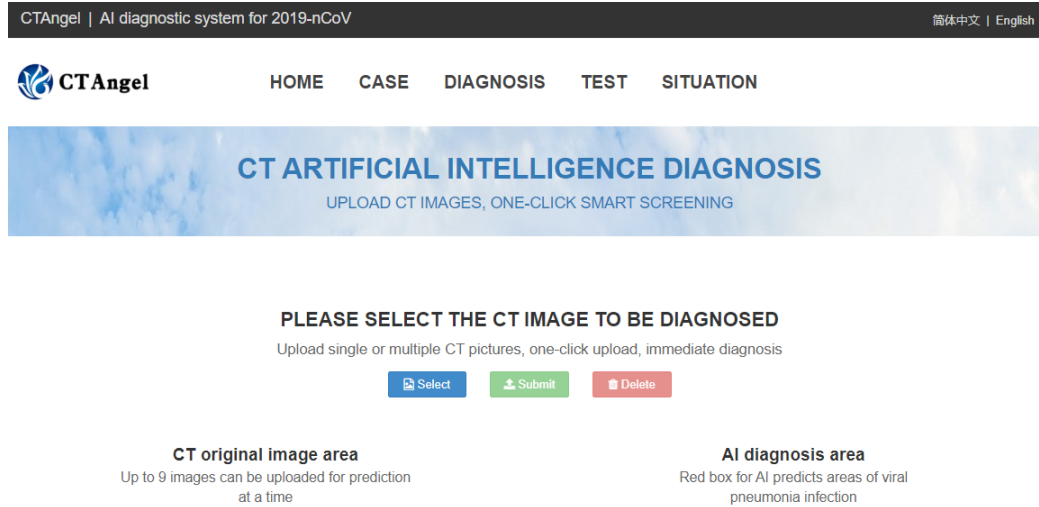
478 showing a mass in the left upper lobe, with burrs seen at the edges, and showing leaf-like growth

479 with vacuoles inside. The third image is a secondary pulmonary tuberculosis, showing a left apical

480 fibrous cord. The fourth image is a bronchiectasis complicated with infection, showing

481 bronchodilation and expansion, cystic changes, and surrounding patches of infection. The fifth

482 image shows normal lungs.



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484 **Figure 5. Main interface of the open-access artificial intelligence platform which provides**

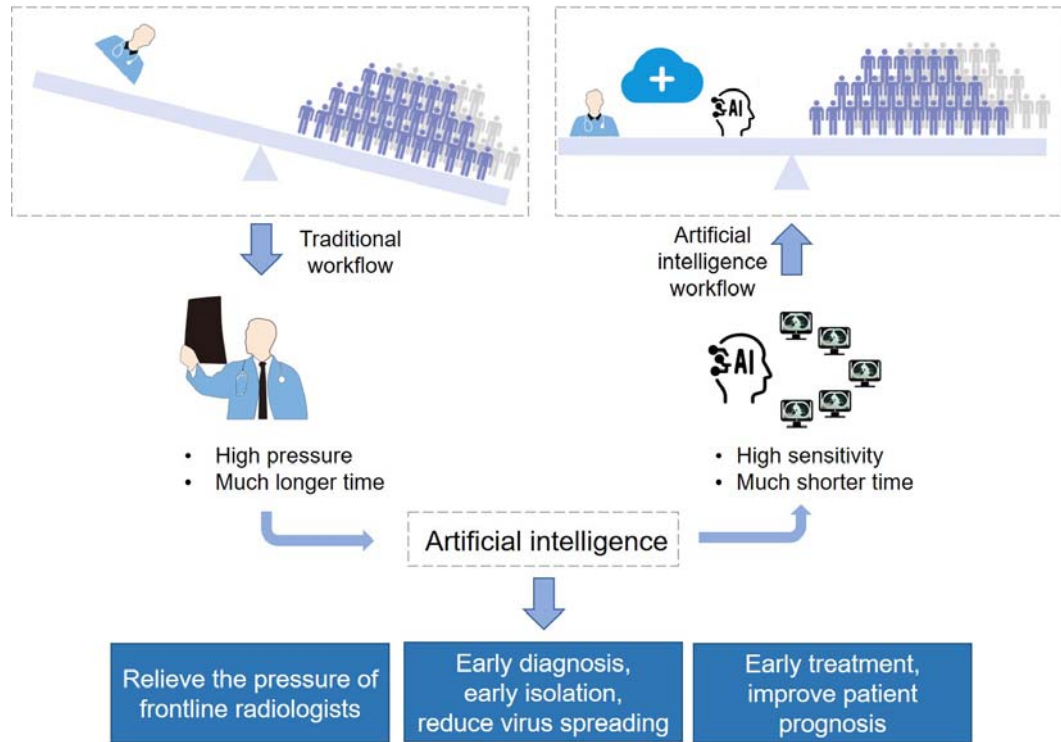
485 **fast and sensitive assistance for detecting COVID19 pneumonia.**

486 (<http://121.40.75.149/znyx-ncov/index>)

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491 **Figure 6. Abstract diagram.** Computed tomography (CT) is the most efficient modality for

492 screening and clinically diagnosing COVID-19 pneumonia. However, compared to the needs of

493 the patients, the number of radiologists is quite small. After enrolling artificial intelligence in

494 identifying COVID-19 pneumonia in CT images, the efficiency of diagnosis is greatly improved.

495 The artificial intelligence holds great potential to relieve the pressure of frontline radiologists,

496 accelerates the diagnosis, isolation and treatment of COVID19 patients, and therefore contribute to

497 the control of the epidemic.

498

499 **Supplementary Figure 1. The training curves of UNet++ for extracting valid areas in**

500 **Computed tomography images.**

501 **Supplementary Figure 2. The training curves of UNet++ for detecting suspicious lesions in**

502 **Computed tomography images.**