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Helping healthcare providers to differentiate COVID-19 pneumonia by analyzing digital chest x-rays: role of artificial intelligence in healthcare practice

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1 **Helping the Healthcare Providers to Differentiate Coronavirus Disease 2019 Pneumonias**
2 **by Analyzing Digital Chest X-Rays: Role of Artificial Intelligence in Healthcare Practice**

3

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9

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- 37

38 **Key Points:**

- 39 • The major strength of this study is that it has developed a technology-based tool which
40 can precisely detect COVID - 19 at an early stage and immediately isolate infected
41 patients from the healthy population.
- 42 • This next generation test can be accessed by the healthcare providers remotely and
43 therefore pose a prospect of convenience.
- 44 • The main limitation is that this tool may confuse with other Pneumonias if the quality
45 of chest image is too low. Moreover, it focuses only on detecting whether or not it is
46 COVID - 19, but not the severity of the disease.
- 47

48 **Keywords:** COVID - 19, Detection, Chest X-Ray, Artificial Intelligence, Bangladesh.

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Abstract

Background: Detecting the Coronavirus Disease 2019 pneumonia, and differentiating it from other Community Acquired Pneumonias has been has been a challenging task for the healthcare providers since the pandemic begun. We therefore aim to develop and evaluate a simple, non-invasive tool to accurately detect COVID – 19 by using digital chest X-rays.

Methods: This is a retrospective, multi-center study where deep learning frameworks were used to develop the system architecture of the diagnostic tool. The tool was trained and validated by using data from the Github database and two hospitals in Bangladesh. Python programming was used to calculate all statistical estimates. Ethical approval was obtained, and administrative permission taken from the participating hospitals.

Results: This study revealed that the artificial intelligence- based diagnostic tool was able to detect COVID - 19 accurately by examining the chest X-rays. During the testing phase, the tool could interpret chest X-rays with precision of 0.98, recall/sensitivity 0.97 and F1 score 0.97 for COVID 19. The study evaluated the performance of the tool with real-life data from two hospitals in Bangladesh. The results showed high sensitivity (90%) and specificity (92%) in detecting COVID - 19. The AUC values for COVID - 19 and Pneumonia were 0.91 and 0.87 respectively.

Conclusions: This Artificial Intelligence- based diagnostic tool can offer the healthcare providers an effective means to detect and differentiate COVID – 19 from other forms of pneumonias, thus contributing to reducing the long-term impact of this deadly disease.

76

77 **Background**

78

79 The novel coronavirus, known as severe acute respiratory syndrome coronavirus 2 or SARS-
80 CoV-2, is responsible for coronavirus disease 2019 (COVID – 19) that primarily causes
81 respiratory illnesses of varying severity ranging from common cold to fatal pneumonia [1-3].

82 The virus is highly transmissible which has ravaged the world since it was first identified in
83 late 2019. So far it has affected millions of people, causing global pandemic and incapacitating
84 the healthcare systems [2-5]. Although the SARS-CoV-2 potentially affects multiple organs of
85 the human body, it mainly infiltrates the lower respiratory system triggering inflammatory
86 changes in the lung tissue. Most of these infected patients commonly present with mild fever
87 and dry cough, however, about one-fifth of all infected patients progress to severe pneumonia
88 or even death [1,4-6].

89

90 Detecting COVID - 19 throughout the pandemic has been challenging and daunting task
91 because of shortage of diagnostic tools in many countries. The detection was mostly dependent
92 on a molecular technique called Polymerase Chain Reaction or PCR, which has been the most
93 preferred testing procedure since the beginning of this pandemic. However, as the transmission
94 of COVID - 19 escalated, the health systems of most countries struggled to provide the testing
95 services to its entire population due to diverse technical, financial and logistical barriers [6-8].

96 Moreover, due to similarities of clinical presentations of COVID – 19 with other pneumonias,
97 establishing correct diagnosis poses greater challenges to the health care providers.
98 Accordingly, major medical societies in multiple countries recommended to use chest
99 radiography to diagnose COVID – 19 pneumonia and also to differentiate from other
100 community acquired pneumonias (CAP) [6]. In some cases, computed tomography (CT) scan

101 has also been successfully used to detect COVID – 19 even with a negative PCR test or in
102 patients without symptoms.

103

104 In almost all healthcare practices, clinicians use X-ray images to diagnose pneumonias and
105 other lung diseases. Now a days, digital imaging machines – both static and mobile - are
106 available in all hospitals and diagnostic centers; thus, digital X-rays are widely used for
107 diagnostic purposes. However, the main challenge with the interpretation of the chest X-rays
108 is that it requires a radiologist or a specialist doctor to do the analysis, and thereby can be time-
109 consuming, and logistically inconvenient [6,7]. Moreover, it can become burdensome to the
110 already stretched health system as more and more people are getting sick due to new COVID
111 – 19 variants.

112

113 Use of artificial intelligence (AI) in the medical field is not new. Particularly deep learning
114 method is being widely used in many healthcare settings due to its unique advantages in
115 precisely detecting some complex health conditions, such as Tuberculosis and lung cancer [6-
116 9]. Therefore, we hypothesized that an AI-based tool could be developed and trained to
117 accurately detect COVID – 19 pneumonias and to differentiate them from other types of CAPs
118 by using chest X-rays. In this paper, we present the system architecture of an innovative AI-
119 based tool and the results of its validation and performance in differentiating the COVID – 19
120 from other forms pneumonias.

121

122

123 **Methods**

124

125 *Development and Validation Data Sets*

126

127 We trained our tool to distinguish X-rays of COVID – 19 from other CAPs. We also instructed
128 the tool to isolate the chest radiology with no apparent abnormalities. Total 299 digital X-ray
129 images were utilized to train this AI-based tool. Of them, 89 X-rays were COVID - 19 positive
130 cases, 100 were diagnosed as Pneumonia cases, and 110 X-rays of ‘normal’ patients i.e. X-rays
131 with no chest/lung diseases (Figure 1). The validation was carried out to evaluate the predicting
132 power of the tool by using a sample of 24 chest X-rays of confirmed COVID - 19 patients, 234
133 images of CAPs, and 390 images of ‘normal’ patients.

134

135 Strict selection criteria were applied to select desired quality of chest X-rays. Only digital,
136 Postero-anterior (PA) views of the images were used. For developing the tool, we used chest
137 X-rays of confirmed COVID – 19 cases and the Community Acquired Pneumonias (CAP); and
138 the X-rays of non-pneumonia or ‘normal’ cases. The X-rays of CAPs and ‘normal’ cases were
139 selected randomly who fulfilled the inclusion criteria. Only confirmed SARS-CoV-2 cases
140 were considered, who were anonymous but had a complete record ranging from the
141 identification (ID) number, clinical history, and the final outcomes of treatment. Chest images
142 from any unauthorized sources or of low resolution were discarded.

143

144 We have used chest X-rays from two hospitals in Bangladesh¹ and the COVID -19 X-ray
145 images from the GitHub database [10]. Special attention was given to select X-ray images of

¹ Rangpur Medical College Hospital, Rangpur, Bangladesh; and Cardio Care Hospital, Dhaka, Bangladesh

146 those patients who had a complete trail of demographic and diagnostic history in the dataset.
147 Although we used X-ray images of hospital patients, we had no direct contact with patients.
148 All data were stored in a secure, encrypted database with strict security and privacy protocols
149 in place.

150

151 **(Place Figure 1 here)**

152

153 *Patient and public involvement*

154

155 Although we have used the chest images from a known dataset, we did not directly involve
156 patients or any other human participants. The study protocol was reviewed and approved by
157 the university ethics committee and written permission was obtained from participating
158 hospitals. Moreover, the data used was encrypted and anonymous.

159

160 *Statistical analysis*

161

162 In order to measure sensitivity and specificity, the AI-based tool was validated by randomly
163 uploading data from the above-mentioned three data types. Rigorous statistical analysis was
164 performed and the outputs of each round of validations were observed and recorded. These
165 outputs were then compared with the WHO data set for accuracy and precision. The
166 performance of the tool was analyzed and verified on the basis of standard measures such as
167 sensitivity and specificity, and the receiver operating characteristic (ROC) curve and area under
168 the curve (AUC). Python programming was used to calculate all statistical estimates.
169 Furthermore, we have drawn a ROC curve which is the plot of sensitivity versus 1-Specificity.
170 The AUC was also used for an effective measure of accuracy.

171

172 **Results**

173

174 In this section, we describe the system architecture of the AI-based tool and the results of the
175 comparative performances of three deep learning image classifiers [11-13], which we
176 experimented in this study.

177

178 *Model architectures*

179

180 For developing the system architecture, we examined different deep learning models which
181 were derived from the field of artificial intelligence. These models are basically different
182 architectures of Convolutional Neural Network (CNN) that has been a dominant method in
183 computer vision tasks since the astonishing results were shared on the object recognition
184 competition known as the ImageNet Large Scale Visual Recognition Competition (ILSVRC)
185 in 2012. CNN uses multiple perceptrons that analyze image inputs and are able to segregate
186 the images from one another. Another advantage of using CNN is that it leverages the use of
187 local spatial coherence in the input images, which allow them to have fewer weights as some
188 parameters are shared. This process is found to be efficient in terms of memory and complexity
189 [14]. The basic building blocks of CNN are as follows:

190

191 *Convolution layer*

192

193 In the convolutional layer, a matrix named Kernel is passed over the input matrix to create a
194 feature map for the next layer. We have performed a mathematical operation called convolution
195 by sliding the Kernel matrix over the input matrix. At every location, an element wise matrix

196 multiplication is performed and sums the result onto the feature map. Convolution is a
197 specialized kind of linear operation which can be applied over more than 1 axis. If we have a
198 2- Dimensional image input, I, and a 2-Dimensional kernel filter, K, the convoluted image is
199 calculated as follows:

$$S(i, j) = \sum_m \sum_n I(m, n)k(i - m, j - n)$$

203

204 *Non-Linear activation functions*

205

206 Activation function is a node that comes after the convolutional layer and the activation
207 function is the nonlinear transformation that we do over the input signal. Different activations
208 functions are:

209

- 210 a. ReLU: Rectified linear unit activation function (ReLU) is a piecewise linear
211 function that will output the input if it is positive, otherwise it will output zero.

212

$$213 \quad f(x) = \max(0, x)$$

214

- 215 b. Leaky ReLU is a variant of ReLU. Instead of being 0 when $z < 0$, a leaky ReLU
216 allows a small, non-zero, constant gradient α (Normally, $\alpha = 0.01$)

217

$$218 \quad R(z) = \{z \text{ when } z > 0, \alpha z \text{ when } z \leq 0\}$$

219

- 220 c. Sigmoid takes a real value as input and outputs another value between 0 and 1. It's
221 easy to work with and has all the nice properties of activation functions: it's non-

222 linear, continuously differentiable and it's used in the output layer when the
223 classifier is binary.

224

$$225 \quad S(Z) = \frac{1}{1 + e^{-z}}$$

226

227 *Pooling layer*

228

229 A pooling layer is a new layer added after the convolutional layer, specifically, after a
230 nonlinearity (e.g. ReLU) has been applied to the feature maps output by a convolutional layer.

231 The drawback of the feature map output of a convolutional layer is that it records the precise
232 position of features in the input. This means during cropping, rotation or any other minor
233 changes to the input image will completely result in a different feature map. To counter this
234 problem, we approached down sampling of convolutional layers. Down sampling was achieved
235 by applying a pooling layer after nonlinearity layer. Pooling helped to make the representation
236 become approximately invariant to small translations of the input. Invariance to translation
237 means that if we translate the input by a small amount, the values of most of the pooled outputs
238 do not change (Figure 2).

239

240 **(Place Figure 2 here)**

241

242 *Fully Connected Layer*

243

244 At the end of a convolutional neural network, the output of the last pooling layer acts as input
245 to the Fully Connected Layer. There can be one or more of these layers. Fully connected means
246 that every node in the first layer is connected to every node in the second layer.

247

248 *Development of system architecture*

249

250 In this study, we applied three different architectures of CNN such as: i) Visual Geometry
251 Group Network 16 (VGG16), ii) Residual Networks 50 (ResNet50), and iii) Depthwise
252 Convolution Neural Network (CNN) to assess their comparative performances in detecting
253 COVID – 19 (Figure 3). The results of each of these tests were recorded.

254

255 *Firstly*, we studied the performance of VGG16 in distinguishing COVID – 19 and other
256 Pneumonias. VGG16 is a convolutional neural network architecture. It was initially developed
257 by the Oxford Robotics Institute's Karen Simonian and Andrew Zisserman which was first
258 submitted to the 'ImageNet Large Scale Visual Recognition Challenge 2014 (ILSVRC2014)'
259 where it performed very well and achieved 92.7% top-5 accuracy [15]. The first and second
260 convolutional layers consist of 64 feature kernel filters and the size of the filter is 3×3. As the
261 input image (RGB image with depth 3) passes into the first and second convolutional layer,
262 dimensions change to 224x224x64. Then the resulting output is passed to the max pooling layer
263 with a stride of 2. The third and fourth convolutional layers are of 124 feature kernel filters and
264 size of filter is 3×3. These two layers are followed by a max pooling layer with stride 2 and the
265 resulting output will be reduced to 56x56x128. The fifth, sixth and seventh layers are
266 convolutional layers with kernel size 3×3. All three use 256 feature maps. These layers are
267 followed by a max pooling layer with stride 2. Eighth to thirteen are two sets of convolutional
268 layers with kernel size 3×3. All these sets of convolutional layers have 512 kernel filters. These
269 layers are followed by a max pooling layer with stride of 1. Fourteen and fifteen layers are fully
270 connected hidden layers of 4096 units followed by a softmax output layer (Sixteenth layer) of
271 1000 units.

272

273 *Secondly*, we deployed ResNet-50 which is also a convolutional neural network¹⁴ that is 50
274 layers deep as below:

- 275 • At first there is a convolution with a kernel size of $7 * 7$ and 64 different kernels all
276 with a stride of size 2 giving us 1 layer.
- 277 • Next we got max pooling with also a stride size of 2.
- 278 • In the next convolution, there was a $1 * 1,64$ kernel following this a $3 * 3,64$ kernel and
279 at last a $1 * 1,256$ kernels, These three layers were repeated in total 3 times so giving
280 us 9 layers in this step.
- 281 • Next we saw kernel of $1 * 1,128$ after that a kernel of $3 * 3,128$ and at last a kernel of
282 $1 * 1,512$ this step was repeated 4 times so giving us 12 layers in this step.
- 283 • After that there was a kernel of $1 * 1,256$ and two more kernels with $3 * 3,256$ and $1 * 1,$
284 $1,1024$ and this is repeated 6 times giving us a total of 18 layers.
- 285 • And then again a $1 * 1,512$ kernel with two more of $3 * 3,512$ and $1 * 1,2048$ and this
286 was repeated 3 times giving us a total of 9 layers.
- 287 • After that we did an average pool and ended it with a fully connected layer containing
288 1000 nodes and at the end a softmax function so this gives us 1 layer.
- 289 • So totaling this it gave us a $1 + 9 + 12 + 18 + 9 + 1 = 50$ layers Deep Convolutional
290 network.

291

292 This network allowed us to load a pre-trained version of the network trained on more than a
293 million images from the ImageNet database. As a result, the network has learned great feature
294 representations for a wide range of images.

295

296 *Thirdly*, we examined the performance of Depthwise CNN which is another deep learning,
297 artificial intelligence function that mimics the functioning of the human brain in processing
298 data and creating models for decision-making use. The Depthwise convolution model is a 2D
299 convolution which helps to reduce overfitting when the number of parameters is high. It deals
300 not just with spatial dimension but with depth dimension as well as the number of channels.
301 What we do here is apply a 2D depth filter at each depth level of input tensor in our dataset so
302 that we have 3*4095*4095(input channels, max width, max height). The filter we have used to
303 extract feature is 3*3*3. So the Depthwise convolution will break the image and filter into 3
304 different channels and then convolve the corresponding channel and then stack them back.
305 After that we used 1*1 filter to cover the dimension. Here the amount of parameters is reduced
306 by the number of input channels. The feature from Depthwise spatial convolutional model send
307 to fully connected layers where the output layer consists of 3 nodes (Covid-19, CAP, and
308 Normal)

309
310 **(Place Figure 3 here)**

311

312 *Finalization of System Architecture*

313

314 The comparative analysis showed that VGG16 performed better results among the three deep
315 learning image classifiers used in this study (Figure 4). It was observed that the VGG16 was
316 able to read Covid-19 images more accurately compared to ResNet50 and Depthwise CNN
317 with precision of 0.98, recall/sensitivity 0.97 and F1 score 0.97 (Table 1). Once the tool was
318 fully trained, the model was recalibrated and refined based on the outputs of the testing process.
319 The whole process was random and was meticulously monitored and recorded. After several
320 repetitions, the model was finally ready for validation.

321

322 Table 1: Comparison of used deep learning models

323

Type of Data	Sensitivity %	Specificity %	AUC
VGG 16	97	99	98
ResNet50	95	98	97
Depthwise CNN	96	97	97

324

(Place Figure 4 here)

325

326

327 *Performance evaluation of the Tool*

328

329 The age group of the study population and patients of data sources was between 20 and 90
330 years.

331

332 The tool was found to be very quick in processing any given X-ray image. On an average, it
333 took 5.7 seconds to complete while we ran the tests through our server. It was also observed
334 that the model was able to accurately detect COVID - 19 as the tool/model detected 96% of
335 cases as true positive. On the other hand, it exhibited a high power of rejecting non COVID –
336 19 cases as specificity is approximately 98%. In addition, the results showed low false positives
337 and false negatives, which gave us confidence about the accuracy of the model. Similarly, the
338 model could also identify pneumonia and normal images fairly accurately (Table 2). It is
339 important to note that the proposed model has achieved a low rate of false negatives, as a high
340 rate of false negative diagnoses may have moral, ethical, financial and social implications.

341

342 Table 2: Validation results of the Tool

343

Type of Data	Sensitivity %	Specificity %	AUC
COVID – 19 (n=24)	90	92	91
Normal (n=234)	8	8	84
Pneumonia (n=390)	86	88	87

344

345 We have evaluated our AI-based tool for detecting COVID - 19 by using chest X-rays from
346 confirmed Bangladeshi COVID - 19 cases. The evaluation results showed high sensitivity
347 (90%) and specificity (92%) in detecting COVID - 19. The AUC values for COVID - 19 and
348 Pneumonia were 0.91 and 0.87 respectively (Table 2).

349

350 Both ROC and AUC curves played a central role in evaluating diagnostic ability of tests to
351 show the true state of disease condition, finding the optimal cut off values (close to sensitivity
352 100%), and AUC was close to 1. Figure 5 reveals that ROC and AUC as alternative diagnostic
353 tasks performed well in this case.

354

(Place Figure 5 here)

356

357 *(Note: Class 0 is covid-19, class 1 is Normal and class 2 is Pneumonia)*

358

359 While evaluating the model, it has been observed that there is a strong relationship between
360 pneumonia and having a COVID - 19 (figure 6). This may partly be explained by the fact that
361 COVID - 19 causes serious pneumonia.

362

363 **(Place Figure 6 here)**

364

365 *Operationalizing the Tool*

366

367 We have developed a website to operationalize the AI-based tool (www.helpus.ai). The website
368 can be accessed and used by health facilities or medical professionals both domestically and
369 internationally, provided they have computer access. New users will need to register and have
370 their account verified before they will be granted a login ID to access the website. A webmaster
371 will monitor and manage the system in order to protect the system from unscrupulous use. A
372 short online training program is included to enable new users to use the detection tool. The
373 system is user-friendly and consists of a minimum interface. Authorized users can upload the
374 digital X-ray image to be tested on the website. The program will detect if a valid chest X-Ray
375 image (PAV) has been uploaded otherwise it will reject it. If a valid image has been submitted
376 the results of the test will be displayed instantly. Our system is tuned to display “positive” or
377 “negative” results along with a percentile probability of that image whether it is “COVID - 19”,
378 “Pneumonia” or “Normal”. The entire process can take a few seconds to a couple of minutes,
379 depending on the computer and connection speed of the user. The data provided by the users
380 can be stored in our cloud-based server while maintaining security and privacy protocols. The
381 data can be retrieved by users and are accessible by the research team for future analysis.

382

383

384 **Discussion**

385

386 The pace of transmission of different variants of COVID – 19 is so exponential that many
387 health systems are facing an uphill battle to cope with the testing of COVID – 19 and detection
388 of COVID – 19 induced pneumonias [1,6]. Traditionally, the chest X-ray is part of the routine
389 check-up for patients with respiratory symptoms, and digital imaging is widely accessible even
390 in resource-poor healthcare settings. Therefore, integrating the proposed AI-based tool to help
391 the healthcare providers to analyse combination of chest radiography in their existing general
392 practice. Our results provide evidence that this AI-based tool has the potential to improve the
393 quality and accuracy of the radiologic interpretation of COVID - 19 pneumonias. We also
394 believe that it can be acceptable to both healthcare workers and the patients, and can become
395 relatively inexpensive compared to other diagnostic methods. Intensive efforts has been made
396 in recent years to generate evidence which suggest that the examination of radiologic images
397 was found to be an effective method for diagnosing COVID – 19. Others have demonstrated
398 that AI technology was able to read chest X-rays and Computed Tomography (CT) scans to
399 detect different lung diseases, especially pneumonias, lung cancers and Tuberculosis [6-9, 16-
400 18]. However, the main challenges are either to get a radiologist to interpret the chest
401 radiographs, or even inability to differentiate COVID – 19 pneumonias from other CAPs if the
402 radiologist is not trained in reading the COVID – 19 radiographs. In our study, we demonstrated
403 that a fully developed AI-based tool can read any chest radiographs with high precision. We
404 have also operationalized the tool via a user-friendly software which instantly display the
405 correct result once the chest X-ray is scanned. The software can be operated by any service
406 provider having basic IT knowledge. During evaluation, our AI-based tool showed excellent
407 performance with high sensitivity (90%) and specificity (92%) in detecting COVID – 19

408 pneumonias. The AUC values for COVID - 19 and Pneumonia were 0.91 and 0.87 respectively.
409 Our result corroborates with the outcomes of other similar efforts where machine learning
410 models were trained to diagnose COVID – 19. However, most of those studies were limited in
411 their scope and dataset. Only couple of studies had relatively larger data set with varying degree
412 of precision. Some studies also trained the machine learning tools to detect COVID - 19 by
413 analyzing CT scans.

414

415 In Bangladesh, the digital imaging is available in almost everywhere, both in rural and urban
416 clinics. Due to technological advancements, good quality digital imaging machines are also in
417 good supply. Even there are mobile imaging units in the most remote areas of the country,
418 which allows the clinicians to get the chest imaging done as and when they need. In our study,
419 we systematically validated the tool by using the real-life data from two hospitals in
420 Bangladesh. We also included a good number of chest X-rays of random patients with no know
421 chest symptoms to train and test our tool to differentiate the non-pneumonia or ‘normal’ cases.

422

423 During the testing and validation, our AI-based tool performed very well to identify COVID -
424 19 by analyzing 2D chest radiology PA view. We have further evaluated the AI tool by using
425 chest X-rays of COVID – 19 patients from two Bangladeshi hospitals. We demonstrated that
426 our tool had high sensitivity and specificity which conforms to previous studies [6-9, 16-18].
427 However, the uniqueness of our model is that it is simple and is able to differentiate three
428 scenarios – COVID – 19 pneumonias, CAPs, and those with no obvious abnormalities; by
429 analyzing readily available digital chest X-rays instead of CT scans which, in turn, could easily
430 be integrated within the regular medical practice.

431

432 Although our AI-based tool was able to accurately detect COVID - 19, this research has some
433 limitations. As COVID - 19 is caused by a type of coronavirus, it may produce similar changes
434 in the chest imaging as of CAP. This tool may sometimes give incorrect results only if the
435 image quality is too poor. However, during our validation process, it consistently produced
436 highly accurate results for randomly selected X-ray images. Another limitation was that due to
437 the limited availability of data, we were unable to extensively evaluate the tool with real-time
438 Bangladeshi data. Lastly, the tool focuses only on detecting the existence of COVID - 19, not
439 the severity of the disease.

440

441 **Conclusion**

442

443 In this study, we developed a simple, non-invasive AI based tool for the diagnosis of COVID
444 – 19 pneumonias by using traditional chest X-rays, which can assist the government and the
445 private healthcare workers who are attempting to triage both symptomatic and asymptomatic
446 COVID – 19 patients. We demonstrated that our AI-based tool was effective to detect COVID
447 - 19 and could differentiate COVID - 19 from other CAPs by analyzing the chest X-rays.
448 Therefore, it gives a glimpse of hope to the policy-makers and service providers who are
449 striving for an alternative diagnostic tool to screen, detect and triage the mass population for
450 COVID - 19. However, further validation of this tool may be needed with larger datasets before
451 operationalizing it nationwide.

452

453

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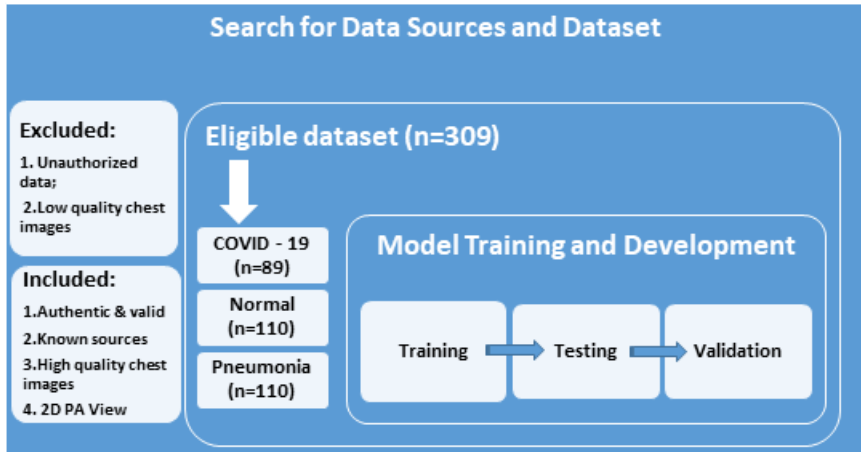
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503 **List of Figures:**

504

505 **1. Figure 1: Data used to train the model.**



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507 **2. Figure 2: Types of pooling**

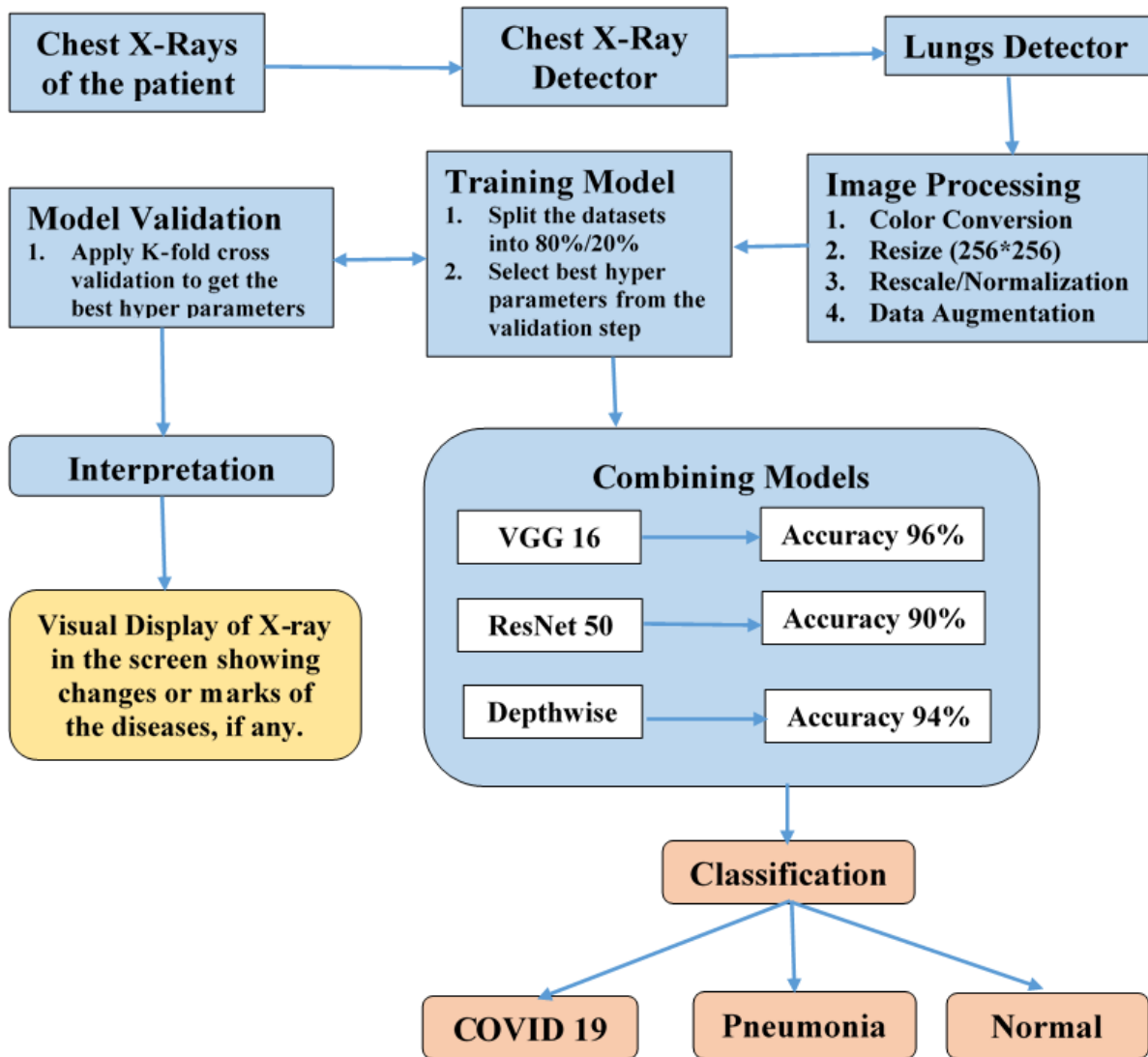


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511 3. Figure 3: System architecture.

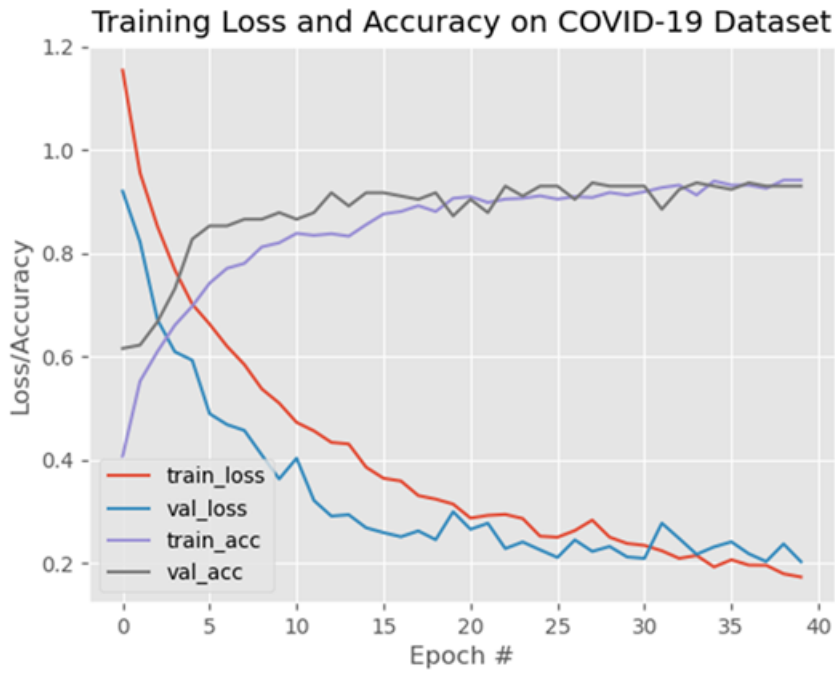


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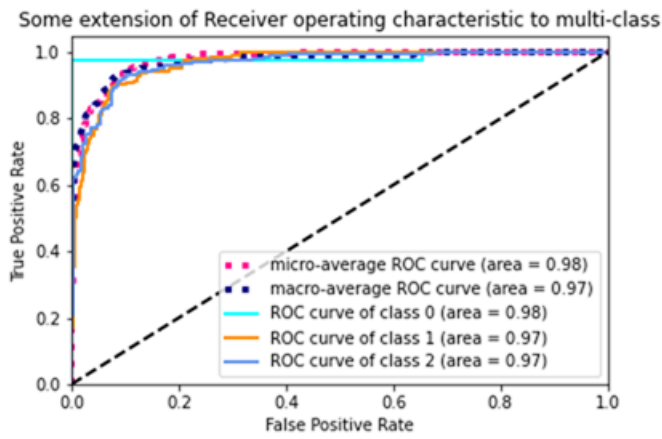
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515 **4. Figure 4: Power of VGG16 in detecting COVID-19 images accurately.**



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517 **5. Figure 5: ROC and AUC curves for the diagnostic tests.**

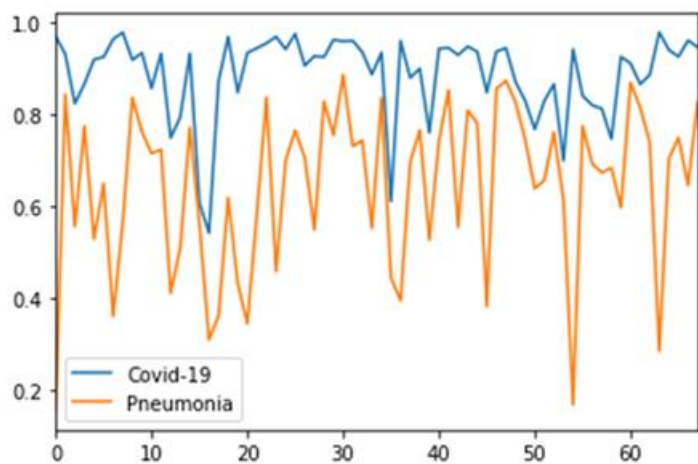


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521 **6. Figure 6: Relationship between Covid-19 and Pneumonia.**



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525 **Declarations:**

526 **Ethical considerations**

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528 The research protocol has been approved by the Research Ethics Committee, Faculty of Allied
529 Health Sciences, Daffodil International University (FAHS-REC, DIU) and participating
530 hospitals. The ethics ID number is FAHS-REC/DIU/2020/1002. Only publicly available data
531 were used, and no identifying participant information was obtained.

532

533 **Data Availability Statement:**

534 The data that support the findings of this study are openly available in Github at
535 <https://github.com/ieee8023/covid-chestxray-dataset>. The local hospital data that support the
536 findings of this study are available from the corresponding author upon reasonable request.

537

538 **Conflicts of Interest:** The authors have declared no conflicts of interests.

539

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542

543 **Author Contributions:**

544

545 Abu Naser Zafar Ullah (ANZU) is responsible for the design, planning and leading the study.
546 ANZU drafted the article, on which all authors made important contributions. Md. Habibur
547 Rahman (HR), Shaikh Muhammad Allayear (SMA), Mohammed Liakwat Ali Khan (LAK)
548 and Sheikh Md. Faysal (SMF) designed the system architecture and participated in collection,

549 extraction, analysis and interpretation of the data. SMA contributed to the technical design of
550 the software and revised the methods section of the article. NU participated in the collection
551 and extraction of local data. Hafiz TA Khan (HTAK) and A B M Alauddin Chowdhury (AC)
552 contributed to the methodology of the study especially in sampling and statistical analysis.
553 ANZU led the process of analysis and interpretation of findings with active contribution from
554 all authors. All authors have revised the article for important intellectual content, and approved
555 the final version of the article for publication.

556

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559