Artificial Intelligence for COVID-19 Outbreak Screening

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Artificial Intelligence (AI)
A subfield of computer science

• AI is any machine that simulates aspect of learning or any other feature of human intelligence (John McCarthy, 1956);

• AI is the theory and development of computer systems able to perform tasks normally requiring human intelligence;

• AI is any system able to pass the Turing test.
What is Machine Learning (ML)?

• Field of study that gives computers the ability to learn without being explicitly programmed. (Arthur Samuel);

• Study of algorithms that improve their performance $P$ at some task $T$ with experience $E$ as we have well defined task $<P,T,E>$. (Tom Mitchell).
What is Deep Learning (DL) ?

- DL methods are ML methods based on learning data representations. They are usually related to the training of neural networks with many layers (>100);
- Fast advances during the last decade, basically related to the Big Data boom and cheap GPU hardware;
- First developed as an applied then as a theoretical field.
AI Subfields:

- Expert System
  - Deep Learning
  - Supervised
  - Not Supervised

- Machine Learning
  - Supervised
  - Not Supervised
- Robotics
  - Extraction of content
  - Classification
  - Translation by machine
  - Answer to questions
  - Creation of content

- Natural Language Processing
  - Image recognition
  - Computer Vision
  - Oral to Written translation
  - Written to Oral translation

- Machine Vision

Mathematical model for a neuron

Perceptron

Input from other neurons

Dendrites

Linear combination of inputs and weights

Non-linear Activation function

Output to other neurons

Human brain

10^{11} neurons = 100 billion

<table>
<thead>
<tr>
<th>Structure</th>
<th>Types of Decision Regions</th>
<th>Exclusive-OR Problem</th>
<th>Classes with Meshed regions</th>
<th>Most General Region Shapes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single-Layer</td>
<td>Half Plane Bounded By Hyper plane</td>
<td>A B</td>
<td>B A</td>
<td>B</td>
</tr>
<tr>
<td>Two-Layer</td>
<td>Convex Open Or Closed Regions</td>
<td>A B</td>
<td>B A</td>
<td>B</td>
</tr>
<tr>
<td>Three-Layer</td>
<td>Arbitrary (Complexity Limited by No. of Nodes)</td>
<td>A B</td>
<td>B A</td>
<td>B</td>
</tr>
</tbody>
</table>

Abin – Roozgard, “Convolutional Neural Networks”, lectures in Neural Networks.
Multi-layer perceptron and image processing

- One or more hidden layers
- Sigmoid activations functions

- Input image: 16 x 16
- Input layer: 256 nodes
- Hidden layer: 100 nodes
- Output layer: 26 nodes
Drawbacks of previous neural networks

- The number of trainable parameters becomes extremely large
Drawbacks

• Little or no invariance to shifting, scaling, and other forms of distortion

154 input change from 2 shift left

77 : black to white
77 : white to black

Shift left 1 pixel

154 input change from 2 shift left

77 : black to white
77 : white to black
Drawbacks

- Little or no invariance to shifting, scaling, and other forms of distortion
Drawbacks

• the **topology** of the input data is completely ignored, especially working with **raw data**
Drawbacks

• The increase in spatial resolution and levels intensity for each pixel results in an exponential increase in complexity.

Black and white patterns: \(2^{32 \times 32} = 2^{1024}\)

Gray scale patterns: \(256^{32 \times 32} = 256^{1024}\)

32 X 32 input image
Convolution Neural Networks (CNN)

- CNN are **neurobiologically** motivated by the findings of locally sensitive and orientation-selective nerve cells in the visual cortex;
- A network structure that implicitly extracts relevant features;
- CNN are a special kind of **multi-layer neural networks**.
The mammalian visual cortex is hierarchical


Convolution Neural Networks (CNN)

- CNN is a feed-forward network that can extract topological properties from an image;
- Like almost every other neural networks they are trained with a version of the backpropagation algorithm;
- Convolutional Neural Networks are designed to recognize visual patterns directly from pixel images with minimal preprocessing;
- They can recognize patterns with extreme variability (such as handwritten characters).
Classification vs. CNN

- **Classification**
  - Pre-processing for feature extraction → \( f_1 \ldots f_n \) → Classification
  - Input → \( f_1 \) → \( f_2 \) → Output

- **Convolutional Neural Networks**
  - Feature extraction → Shift distortion invariance → Classification
  - Input → Output
CNN’s Architecture

Feature maps

Input image

Feature extraction layer

Convolution layer

Shift and distortion invariance or

Subsampling layer

C

S
Feature extraction layer or Convolution layer

• It detects the same feature at different positions in the input image.
Feature extraction

Convolve with

Threshold

Convolve with
Threshold
Feature extraction

- **Shared weights**: all neurons in a feature share the same weights;

- In this way all neurons detect the same feature at different positions in the input image;

- **Reduce the number of free parameters.**
Feature extraction

- If a neuron in the feature map fires, this corresponds to a match with the template.
• the **subsampling** layers reduce the spatial resolution of each feature map

• By reducing the **spatial resolution** of the feature map, a **certain degree of shift and distortion** invariance is achieved.

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![Diagram of subsampling layers](image)
Convolutional Neural Networks

- **Weight sharing** (convolution) + Subsampling (pooling)
  - Reduce the # of parameters
  - Translational invariance

![Diagram showing convolutional layers and pooling operations](image-url)
1. Input is modeled using real randomly selected weights;

2. Calculate the output for every neuron from the input layer, to the hidden layers, to the output layer;

3. Calculate the error in the output $E_{rr}$

4. Travel back from the output layer to the hidden layer to adjust the weights such that the error is decreased;

5. Keep repeating the process until the desired output is achieved.
Example: LeNet5

- **LeNet 5 Architecture**
  - raw image of $32 \times 32$ pixels as input
  - $C_1, C_3, C_5$: Convolutional layer.
    - $5 \times 5$ Convolution matrix.
  - $S_2, S_4$: Subsampling layer.
    - Subsampling by factor 2.
  - $F_6$: Fully connected layer (sigmoid activation function).

Example: LeNet5

- ~187,000 connections.
- ~14,000 trainable weight.

Input image 32 x 32

C1: 6x28x28  S2: 6x14x14  C3: 16x10x10  S4: 16x5x5  C5: 120  F6: 84

RBF: output 10

http://yann.lecun.com/exdb/lenet
Example: LeNet5
Deep Learning = Learning Hierarchical Representations

- It’s deep if it has more than one layer of non-linear feature transformation.

**FACES**

- **Low-Level Feature**
  - Patterns of local contrast

- **Mid-Level Feature**
  - Face features

- **High-Level Feature**
  - Faces

- **Trainable Classifier**

**Applications**

- **Image recognition**: pixel -> edge -> part -> object
- **Text**: char -> word -> word group -> clause -> sentence -> story
- **Speech**: sample -> spectral band -> sound -> ... -> phone -> phoneme -> word ->
you should listen to your dad

Sentence matrix 6x5

3 region sizes (4,3,2)
2 filters/region size
Totally 6 filters

2 feature maps for each region size

6 univariate vectors concatenated together to form a single feature vector

2 classes

D=5

Convolution

Max Pooling

SoftMax

Deep Learning based NLP
AI in Healthcare

• AI is a powerful tool and a partner
  – **Man + Machine** = enhanced human capabilities (AMA, 2018)

• AI can help human
  – Unlock the power of big data and gain insight into patients;
  – Support evidence-based decision making, improving quality, safety, and efficiency;
  – Coordinate care and foster communication;
  – Improve patient experience and outcomes;
  – Deliver value and reduce costs;
  – Improve health system performance & optimization.
Human-machine Partnership in Healthcare

Improving effectiveness
- Quality
  - Experience
  - Outcomes
- Safety
  - Ways to ensure
  - Patient safety
- Efficiency
  - Usability
  - Productivity
- Access to care
- Controlling costs

AI-powered automation
- Machine learning
  - Supervised learning
  - Unsupervised learning
  - Reinforcement learning
- Natural language processing
  - Statistical vs. rule-based NLP
- AI voice technology
  - Clinical voice documentation
  - Voice nursing assistants
- Medical robotics
Supervised Learning

• Most AI successes in healthcare are achieved through supervised learning;

• Identifying the underlying structure/patterns of data and trying to map input variables into discrete categories;

• Data-driven clinical decision support:
  – Diagnostic analysis using medical imaging (e.g., CT-scan, X-rays, MRI procedures);
  – Making medical diagnosis based on the symptoms;
  – Designing and selecting treatments based on biomarkers or other attributes;
  – Identifying at-risk groups based on health-related factors and social determinants.
Supervised Learning: Classification problem

Identifying different types of diseases

CheXpert: A large dataset of chest X-rays and competition for automated chest x-ray interpretation (Launched in 2019 by Stanford university)

<table>
<thead>
<tr>
<th>Rank</th>
<th>Date</th>
<th>Model</th>
<th>AUC</th>
<th>Num Rods Below Curve</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Sep 01, 2019</td>
<td>Hierarchical-Learning-V1 (ensemble) Vingroup Big Data Institute <a href="https://arxiv.org/abs/1911.06475">https://arxiv.org/abs/1911.06475</a></td>
<td>0.930</td>
<td>2.6</td>
</tr>
<tr>
<td>2</td>
<td>Oct 15, 2019</td>
<td>Conditional-Training-LSR ensemble</td>
<td>0.929</td>
<td>2.6</td>
</tr>
<tr>
<td>4</td>
<td>Oct 10, 2019</td>
<td>YWW(ensemble) J&amp;NNU <a href="https://github.com/fhealthcare/Chexpert">https://github.com/fhealthcare/Chexpert</a></td>
<td>0.929</td>
<td>2.8</td>
</tr>
<tr>
<td>5</td>
<td>Oct 17, 2019</td>
<td>Conditional-Training-LSR-V1 ensemble</td>
<td>0.929</td>
<td>2.6</td>
</tr>
</tbody>
</table>

CheXpert dataset:
- 224,316 chest radiographs of 65,240 patients

Phenotype findings:
- No Finding
- Enlarged Cardiomegaly
- Support Devices
- Fracture
- Lung Opacity
- Pleural Other
- Pleural Effusion
- Pneumothorax
- Edema
- Consolidation
- Atelectasis
- Lesion
- Pneumonia
AI to distinguish COVID in CT Exams

- To extract visual features from chest CT exams for the detection of: **COVID-19**, Community acquired pneumonia (CAP) and other non-pneumonia;

- 4,356 CT Exams, based on **Resnet50**, training set 90%, test 10%

AI to distinguish COVID in Chest X-Ray Exams

Chest X-Ray

Chest CT

Chest CT is the gold standard image modality for detecting COVID-19.

Motivation: Chest CT is not available in some health centers in comparison with X-Ray, especially in low income countries.
AI to distinguish COVID in Chest X-Ray Exams

Feature Extraction

1\textsuperscript{st} order Histogram
2\textsuperscript{nd} order Texture
Higher-order spectrum

Radiomic Features

Associative Analysis

Radiomic Features

Clinical Endpoints (e.g., Covid-19 vs. Other Pneumonia)

AI to distinguish COVID in Chest X-Ray Exams

Discovery Datasets
- 29 patients with COVID-19 provided by the Italian Society of Medical and Interventional Radiology
- 127 cases of pneumonia non-related to COVID-19 from the Spanish chest XR cohort (PadChest dataset)
- 39 patients with pneumonia non-related to COVID-19 from the National Library of Medicine, National Institutes of Health (OpenI dataset)

Validation
- 32 patients from around the world. In this set, images and clinical data were initially collected from the literature by researchers of the University of Montreal
- Then it was completed with follow-up data (survival time, imaging and event dates) by us to perform the radiomic analysis
- From those 32 patients, 20 had the diagnosis confirmed for COVID-19 by RT-PCR, and 12 from a different etiology

AI to distinguish COVID in Chest X-Ray Exams

Top features ROC curve

## Summary of AI methods for COVID-19 diagnosis using radiology images

<table>
<thead>
<tr>
<th>Ref.</th>
<th>DATA</th>
<th>AI Method</th>
<th>Performance</th>
</tr>
</thead>
<tbody>
<tr>
<td>[7]</td>
<td>970 CT volumes of 496 patients with confirmed COVID-19 and 1,385 negative cases</td>
<td>2D deep CNN</td>
<td>ACC 94.98% and AUC 97.91%</td>
</tr>
<tr>
<td>[8]</td>
<td>1,341 normal, 1,345 viral pneumonia, and 190 COVID-19 chest X-ray images</td>
<td>AlexNet [18], ResNet-18 [3], DenseNet-201 [19], SqueezeNet [20]</td>
<td>ACC 98.3%</td>
</tr>
<tr>
<td>[9]</td>
<td>5,941 Posterior-anterior chest radiography images across 4 classes (normal: 1,583, bacterial pneumonia: 2,786, non-COVID-19 viral pneumonia: 1,504, and COVID-19: 68)</td>
<td>Drop-weights based Bayesian CNNs</td>
<td>ACC of 89.92%</td>
</tr>
<tr>
<td>[10]</td>
<td>1,065 CT images (325 COVID-19 and 740 viral pneumonia)</td>
<td>Modified INCEPTION transfer-learning model</td>
<td>Sensitivity 0.67, Specificity 0.83, and ACC 79.3%</td>
</tr>
<tr>
<td>[11]</td>
<td>16,756 chest radiography images across 13,645 patient cases from two open access data repositories</td>
<td>A deep CNN, namely COVID-Net</td>
<td>ACC 92.4%</td>
</tr>
<tr>
<td>[12]</td>
<td>CT images of 1,136 training cases (723 positives for COVID-19) from 5 hospitals</td>
<td>A combination of 3D UNet++ and ResNet-50</td>
<td>Sensitivity 0.97 and specificity 0.922</td>
</tr>
</tbody>
</table>
Supervised Learning: Regression problem

Predicting results within a continuous output

- Predicting inpatient mortality and long length of stay based on EHR Big Data
- Predicting the number of ER patients during a specific period, needed staff and beds based on past data
- Predicting patients’ survival rates based on health conditions, age, and other characteristics
AI hybrid model to predict COVID-19

- Combination of Improve Susceptible–Infected (ISI) model, Natural Language Processing (NLP) module and the Long Short-Term Memory (LSTM) network are embedded to predict COVID-19

Risk estimation for COVID from meta-analysis of symptoms and conditions

- Descriptive statistics of population groups from Singapore ILI study (H1N1, Seasonal Influenza, Influenza-) and Shanghai meta-analysis of patients with COVID-19 (30 retrospective obs. studies) (COVID-19 severe and non-severe)

<table>
<thead>
<tr>
<th>Variable</th>
<th>A(H1N1/2009) (n=547)</th>
<th>Seasonal influenza (n=193)</th>
<th>Influenza Negative (n=1943)</th>
<th>P Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age, y</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0-5</td>
<td>7.9</td>
<td>25.9</td>
<td>10.9</td>
<td></td>
</tr>
<tr>
<td>6-18</td>
<td>41.5</td>
<td>15.5</td>
<td>14.9</td>
<td></td>
</tr>
<tr>
<td>19-35</td>
<td>35.1</td>
<td>21.2</td>
<td>38.6</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>36-60</td>
<td>9.1</td>
<td>14.5</td>
<td>16.9</td>
<td></td>
</tr>
<tr>
<td>≥61</td>
<td>6.4</td>
<td>22.8</td>
<td>18.7</td>
<td></td>
</tr>
<tr>
<td>Male sex</td>
<td>57.4</td>
<td>60.6</td>
<td>54.7</td>
<td>.19</td>
</tr>
<tr>
<td>Fever</td>
<td>79.3</td>
<td>88.1</td>
<td>52.4</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Cough</td>
<td>88.1</td>
<td>81.3</td>
<td>60.7</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Sore throat</td>
<td>53.7</td>
<td>37.3</td>
<td>37.0</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Rhinorrhea</td>
<td>49.9</td>
<td>53.9</td>
<td>37.0</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Myalgia</td>
<td>20.3</td>
<td>15.0</td>
<td>14.6</td>
<td>.005</td>
</tr>
<tr>
<td>Headache</td>
<td>20.8</td>
<td>10.9</td>
<td>13.2</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Dyspnea</td>
<td>0.5</td>
<td>6.7</td>
<td>2.1</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Vomiting</td>
<td>1.1</td>
<td>2.6</td>
<td>1.7</td>
<td>.34</td>
</tr>
<tr>
<td>Diarrhea</td>
<td>0.7</td>
<td>0.0</td>
<td>1.9</td>
<td>.03</td>
</tr>
</tbody>
</table>

Prevalence of symptoms in Pandemic(H1N1/2009), Seasonal Influenza and Influenza Negative groups. Reproduced from [1]

<table>
<thead>
<tr>
<th>Variable</th>
<th>Overall Severity</th>
<th>Severe</th>
<th>Non-severe</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>CFR, % (95%CI)</td>
<td>3.1 (1.9-4.2)</td>
<td>6.0 (4.6-7.3)</td>
<td>0.1 (0.0-0.2)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Fever</td>
<td>79.1 (68.0-90.3)</td>
<td>88.4 (73.1-100.0)</td>
<td>81.4 (62.6-100.0)</td>
<td>0.552</td>
</tr>
<tr>
<td>Cough</td>
<td>58.0 (42.0-74.0)</td>
<td>71.1 (59.2-82.7)</td>
<td>65.7 (57.8-73.5)</td>
<td>0.449</td>
</tr>
<tr>
<td>Fatigue</td>
<td>29.3 (23.4-35.3)</td>
<td>60.3 (39.9-80.8)</td>
<td>44.2 (32.6-55.9)</td>
<td>0.181</td>
</tr>
<tr>
<td>Expectoration</td>
<td>11.5 (9.2-13.9)</td>
<td>37.6 (22.7-52.6)</td>
<td>28.0 (19.3-37.0)</td>
<td>0.281</td>
</tr>
<tr>
<td>Headache</td>
<td>6.0 (4.0-7.9)</td>
<td>11.3 (7.4-15.2)</td>
<td>13.5 (7.6-19.4)</td>
<td>0.542</td>
</tr>
<tr>
<td>Diarrhea</td>
<td>5.7 (3.9-7.5)</td>
<td>5.7 (3.1-8.1)</td>
<td>5.8 (3.3-8.8)</td>
<td>0.957</td>
</tr>
<tr>
<td>Myalgia</td>
<td>3.8 (2.4-5.2)</td>
<td>26.0 (11.4-49.0)</td>
<td>13.1 (8.4-17.8)</td>
<td>0.107</td>
</tr>
<tr>
<td>Shortness of breath</td>
<td>3.5 (2.2-4.9)</td>
<td>35.7 (17.8-53.7)</td>
<td>12.8 (4.7-20.9)</td>
<td>0.023</td>
</tr>
<tr>
<td>Sore throat/Pharyngalgia</td>
<td>3.2 (1.7-4.6)</td>
<td>7.8 (0.0-16.1)</td>
<td>9.7 (4.0-15.4)</td>
<td>0.706</td>
</tr>
<tr>
<td>Nausea or vomiting</td>
<td>2.0 (1.0-2.9)</td>
<td>5.9 (1.1-8.7)</td>
<td>5.7 (2.3-9.0)</td>
<td>0.928</td>
</tr>
<tr>
<td>Chills</td>
<td>1.1 (0.3-3.1)</td>
<td>26.0 (8.9-43.1)</td>
<td>10.9 (4.0-22.9)</td>
<td>0.087</td>
</tr>
<tr>
<td>Nasal congestion/Rhinorhrea</td>
<td>1.1 (0.3-3.1)</td>
<td>2.8 (0.4-5.2)</td>
<td>5.1 (3.8-6.3)</td>
<td>0.097</td>
</tr>
<tr>
<td>Dyspnea</td>
<td>1.0 (0.3-1.7)</td>
<td>4.2 (7.8-80.6)</td>
<td>5.7 (10.6-17)</td>
<td>0.042</td>
</tr>
<tr>
<td>Anorexia</td>
<td>1.0 (0.4-1.7)</td>
<td>14.9 (8.3-21.5)</td>
<td>8.2 (2.4-13.9)</td>
<td>0.135</td>
</tr>
<tr>
<td>Dizziness</td>
<td>0.1 (0.0-0.6)</td>
<td>16.1 (5.3-28.8)</td>
<td>12.1 (5.0-19.2)</td>
<td>0.591</td>
</tr>
<tr>
<td>Any comorbidity, % (95% CI)</td>
<td>37.1 (28.1-46.1)</td>
<td>54.9 (37.2-72.6)</td>
<td>27.6 (19.4-35.8)</td>
<td>0.006</td>
</tr>
<tr>
<td>Specific comorbidity, % (95% CI)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hypertension</td>
<td>19.0 (13.2-24.9)</td>
<td>29.4 (24.8-34.1)</td>
<td>16.1 (11.5-20.7)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Diabetes</td>
<td>8.2 (6.3-10.0)</td>
<td>17.2 (13.4-20.9)</td>
<td>5.8 (3.4-8.1)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>CVD</td>
<td>2.7 (1.4-4.1)</td>
<td>6.9 (3.9-8.8)</td>
<td>2.1 (1.4-2.9)</td>
<td>0.002</td>
</tr>
<tr>
<td>Cerebrovascular disease</td>
<td>1.0 (0.3-3.1)</td>
<td>3.0 (1.2-4.9)</td>
<td>0.9 (0.4-3.3)</td>
<td>0.031</td>
</tr>
<tr>
<td>COPD</td>
<td>0.6 (0.3-0.9)</td>
<td>4.1 (1.8-6.3)</td>
<td>0.7 (0.2-1.1)</td>
<td>0.004</td>
</tr>
</tbody>
</table>

Fatality Rates and Prevalence of symptoms and conditions in Severe and Non-severe COVID patients. Excerpt from [2]

Risk estimation for COVID from meta-analysis of symptoms and conditions

- ReGEN: ReGenerative Estimator Neural Network
  - synthesizer + estimator neural network, inspired by GANs (Goodfellow et al. 2014)

\[
P(Y=S|X) = \sigma f(\beta, X)
\]
\[
f(\beta, X) = \beta_1 x_1 + ... + \beta_M x_M
\]

Parameter adjustment:
- \( \beta_{\text{fever}} \)
- \( \beta_{\text{cough}} \)
- \( \beta_{\text{fatigue}} \)
- \( \beta_{\text{CVD}} \)
COVIDuc applied @ Heart Institute

Risk if COVIDuc > 3,0 !
COVID time series propagation

- Number of cases in each city
- Augmented with flight map (STGCN)
Benefits of AI for healthcare

- **Deep learning** has produced remarkable results for complex real-world problems that involve big data;

- It has the potential to provide **data-driven, evidence-based clinical intelligence** for advancing both biomedical research and service delivery;

- A **new paradigm** to derive insights on biological, diagnostic and therapeutic processes and behaviors from data;

- **Accelerate** the process of digesting and interpreting vast quantities of complex and diverse information.
Limitations of AI for healthcare

• **AI is not an all-purpose solution**
  - For tasks that require common-sense solutions or domain-specific expertise, and situations that are outside of the AI training dataset, it is less applicable.

• **AI Weakness**
  - AI identifies superficial features and patterns, but lacks the understanding of meanings and concepts;
  - Lacks common sense reasoning, general intelligence, and domain knowledge integration;
  - Needs big data, machine learning models are as good as the training data (biases, noises, errors often exist in real-world data);
  - Difficulty to generalize the findings beyond its training dataset.
Limitations of AI for COVID-19 outbreak screening

- AI technologies have penetrated into our daily lives with many successes, they have also contributed to helping humans in the extremely tough fight against COVID-19;

- AI Apps range from medical image diagnosis (Chest Rx & CT), virus transmission modelling and forecasting based on number of cases time series data, text mining and NLP;

- Although various studies have been published, we observe that there are still relatively limited applications and contributions of AI in this battle;

- This is partly due to the limited availability of annotated data about COVID-19 and AI methods normally require large amounts of data for computational models to learn and acquire knowledge.
References


2. Abin – Roozgard, “Convolutional Neural Networks”, lectures in Neural Networks;


Thank you!

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